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Neural Networks and Fuzzy Logic-Based Approaches for Precipitation Estimation: A Systematic Review

Enfoques basados en redes neuronales y lógica difusa para la estimación de la precipitación: una revisión sistemática

Andrés F. Ruiz-Hurtado [1], Viviana Vargas-Franco [2], and Luis O. González-Salcedo [3]

ABSTRACT

Precipitation estimation at the river basin level is essential for watershed management, the analysis of extreme events and weather and climate dynamics, and hydrologic modeling. In recent years, new approaches and tools such as artificial intelligence techniques have been used for precipitation estimation, offering advantages over traditional methods. Two major paradigms are artificial neural networks and fuzzy logic systems, which can be used in a wide variety of configurations, including hybrid and modular models. This work presents a literature review on hybrid metaheuristic and artificial intelligence models based on signal processes, focusing on the applications of these techniques in precipitation analysis and estimation. The selection and comparison criteria used were the model type, the input and output variables, the performance metrics, and the fields of application. An increase in the number of this type of studies was identified, mainly in applications involving neural network models, which tend to get more sophisticated according to the availability and quality of training data. On the other hand, fuzzy logic models tend to hybridize with neural models. There are still challenges related to prediction performance and spatial and temporal resolution at the basin and micro-basin levels, but, overall, these paradigms are very promising for precipitation analysis.

Keywords: precipitation, river basin, neural networks, fuzzy logic, machine learning, fuzzy inference systems

RESUMEN

La estimación de la precipitación a nivel de cuenca hidrográfica es esencial para la gestión de cuencas, el análisis de eventos extremos y dinámicas meteorológicas y climáticas, y el modelado hidrológico. En los últimos años se han empleado nuevos enfoques y herramientas como las técnicas de inteligencia artificial para estimar la precipitación, ofreciendo ventajas sobre los métodos tradicionales. Dos paradigmas principales son las redes neuronales artificiales y los sistemas de lógica difusa, que pueden utilizarse en una amplia variedad de configuraciones, incluyendo modelos híbridos y modulares. Este trabajo presenta una revisión de la literatura sobre modelos híbridos metaheurísticos y de inteligencia artificial basados en procesos de señales, centrándose en las aplicaciones de estas técnicas en el análisis y la estimación de la precipitación. Los criterios de selección y comparación utilizados fueron el tipo de modelo, las variables de entrada y salida, las métricas de desempeño y los campos de aplicación. Se identificó un aumento en el número de este tipo de estudios, principalmente en aplicaciones que involucran modelos de redes neuronales, los cuales tienden a volverse más sofisticados según la disponibilidad y calidad de los datos de entrenamiento. Por otro lado, los modelos de lógica difusa tienden a hibridarse con modelos neuronales. Aún existen desafíos relacionados con el desempeño de las predicciones y la resolución espacial y temporal a nivel de cuenca y microcuenca, pero, en general, estos paradigmas son muy prometedores para el análisis de la precipitación.

Palabras clave: precipitación, cuenca hidrográfica, redes neuronales, lógica difusa, aprendizaje automático, sistemas de inferencia difusa

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Introduction

Precipitation is a critical component of the global water cycle, significantly influencing both climatic and hydrological dynamics [1]. Variations in precipitation intensity have diverse impacts on natural and societal systems [2]. For instance, light rainfall, which soils readily absorb, aids in drought mitigation and boosts agricultural productivity. In contrast, intense downpours frequently result in catastrophic floods and landslides. Consequently, a thorough understanding of the precipitation intensity spectrum is vital for developing specific adaptation strategies. Estimating precipitation at the watershed level is highly valuable for environmental studies, given its role as the primary input in a hydrological system, directly contributing to the analysis of the water budget and related socio-economic and ecosystem interactions [3]. Therefore, accurately estimating precipitation is crucial for understanding meteorological and hydroclimatic processes and their impact on extreme events such as floods and

[1] Mechatronics engineer, Universidad Nacional, Colombia. Affiliation: Master's student in Environmental Engineering at Universidad Nacional, Palmira campus, Colombia. Email: anfruizhu@unal.edu.co

[2] PhD in Environmental Engineering. Affiliation: Universidad Nacional de Colombia, Palmira campus, Colombia. Email: vvargasf@unal.edu.co

[3] PhD in Materials Engineering, Universidad del Valle, Colombia. Affiliation: Universidad Nacional de Colombia, Palmira campus, Colombia. Email: logonzalezsa@unal.edu.co

droughts [4]. Various statistical, analytical, and numerical methods are employed for precipitation estimation [5]. The main approaches involve developing models with explanatory and response variables. Diverse meteorological and physiographical parameters have been included as explanatory variables, and, in recent years, data from remote sensing systems such as satellite images and radars have been progressively incorporated. Significant models like the Global Circulation Model (GCM) and numerical weather prediction (NWP) models are particularly relevant and extensively used on the macroscale [6]. However, more robust and locally adapted models are required for regional and local scales.

Monitoring precipitation enables the acquisition of data for historical analysis, facilitating the development of estimation and prediction models. Measurements are obtained through rain gauges, weather radars, or satellite products with varying spatial and temporal resolutions [7]. The challenges in accurately estimating precipitation on the river basin scale include improving the spatial density of gauges and addressing the coarse resolution of remote sensing products [8]. Furthermore, the evident impacts of climate change in recent years, such as the progressive alteration of precipitation regimes and variations in the frequency and intensity of extreme events (including heavy rain and droughts) underscore the need for more robust and precise estimation at the regional level. Another limiting factor is coupling precipitation with the chaotic behavior of atmospheric dynamics. For example, a known issue in numerical systems corresponds to the errors and significant deviations in predictions caused by even slight changes in initial conditions [9]. Statistically, it has been also recognized that precipitation does not necessarily follow a normal distribution and can be modeled using asymmetrical distributions [10]. Consequently, more effective and powerful approaches, such as the use of artificial intelligence, are being studied to better approximate the correct behavior.

As a result of technological advances in the field of artificial intelligence and related areas such as data science, new approaches for processing and analyzing data for precipitation estimation are being employed. These include machine learning techniques like neural networks and the application of expert knowledge through fuzzy logic [11]. Such techniques provide flexibility and facilitate the development of more robust models for estimating precipitation, given their inherent ability to model complex nonlinear behaviors [12]. Few studies have been found which review artificial intelligence techniques for precipitation assessment, especially in relation to neural networks and fuzzy logic. [13] presented a review on resilient rainfall forecasting models using artificial intelligence techniques, with an emphasis on artificial neural networks (ANNs) as well as on hybrid models including neuro-fuzzy systems.

This document presents a bibliographic review of artificial intelligence techniques used for estimating precipitation. The main objective is to compare ANNs against fuzzy logic models, focusing on the differences between machine learning and expert systems approaches. The methodology for the literature search and the criteria for selection are detailed in the next section. Afterwards, the theorical basis for each method is explained, followed by a discussion of their main applications, and the article concludes with a succinct comparison of the two types of models.

Methodology

We conducted a systematic review to identify relevant studies on rainfall forecasting using artificial intelligence (AI), specifically fuzzy logic, neural networks, and neuro-fuzzy models. A literature search was conducted in the Scopus database, utilizing strategically selected keywords to capture a comprehensive overview of the most relevant studies. With the search criteria presented below, 134 articles were selected for analysis. Each study was systematically reviewed in a specific reading sequence: abstract, conclusion, results and discussion, methodology, and, finally, the introduction. This method facilitated the identification of potential themes and categories in the information presented by each paper.

Selection criteria

The main objective of this systematic review was to analyze the use of AI for precipitation estimation at the river basin level. The main selection criterion was a focus on precipitation analysis, with a preference for river basins and limited to neural networks and fuzzy logic approaches. A secondary objective involved determining and understanding the input and output variables, the model architecture, the performance metrics, and the scope of each case.

Search equations

The set of keywords encompassed terms like *river basin*, *precipitation*, and *artificial intelligence*, with additional specific terms for each technique: *neural networks* and *fuzzy logic*. It should be acknowledged that these terms were consulted in several permutations, including synonyms, nomenclatures, and broader keywords, in order to enhance the search breadth. The following variations were included in the search equations:

- River basin, catchment, watershed
- Precipitation, rainfall, rain estimation, rain rate, precipitation estimation
- Artificial intelligence, machine learning, soft computing
- Artificial neural networks, neural networks, deep learning, machine learning, artificial intelligence
- Fuzzy logic, fuzzy inference systems, expert systems, soft computing, artificial intelligence

Eq. (1) was used for the initial search in Scopus:

(precipitation OR rainfall OR rain OR "precipitation estimation") AND ("river basin" OR watershed OR basin OR catchment) AND ("artificial intelligence" OR "machine learning" OR "neural network" OR "fuzzy logic" OR "soft computing") (1)

Subsequently, a more specialized search was conducted, using several widespread databases (Elsevier, Springer, IEEE) as well as conventional search engines like Google or those oriented towards academic results (Google Scholar), in order to include non-indexed results (e.g., Arxiv). To correctly filter by AI paradigm, Search Eqs. (2) and (3) were employed.

("fuzzy logic") AND (watershed OR "river basin" OR "catchment") AND (precipitation OR "precipitation estimation" OR "rainfall") (2)

("neural network") AND (watershed OR "river basin" OR "catchment") AND (precipitation OR "precipitation estimation" OR "rainfall") (3)

Software tools

VOSViewer [14], [15] was used for the bibliometric analysis, enabling the generation of bibliometric network plots and clustering algorithms. This software facilitates the visual inspection of relevant information from bibliographic metadata such as the authors, keywords, and important terms. Additionally, a thesaurus file was manually elaborated to organize similar concepts within the results of VOSViewer.

Results

The general search using Scopus allowed for the analysis of global concepts. A bibliographic network is shown in Fig. 1, which includes the occurrence of keywords by total count, with the maximum limit of connections set to 200 in order to facilitate visualization. The most important concept found was *ANN*. Other AI techniques like genetic algorithms, random forests, and support vector machines were also visible in the network, highlighting their importance in more recent studies. Fuzzy logic did not seem to be included at first glance, but, after zooming in on the network, this concept indicated a higher similarity to precipitation.

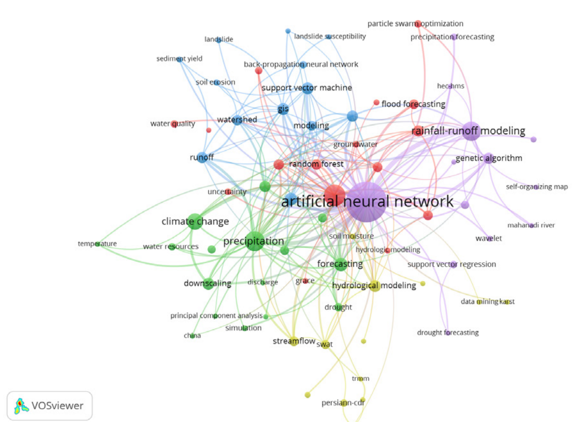

Figure 1. Bibliometric map of the preliminary search
Source: Authors

In the preliminary search, some concepts like *climate change*, *downscaling*, *forecast*, *drought and flood forecasting*, and *hydrological modeling* were also highlighted. Several papers reference *rainfall-runoff modeling*, but *precipitation dynamics* is the only concept that pertains to this review.

The specific search for each approach returned different results, and some representative papers were identified for both neural networks and fuzzy logic according to the selection criteria. It is noteworthy that several of these papers compared their approach against different AI techniques. We prioritized papers using rain gauges and weather stations as the primary data source, as they favor watershed-level analysis. Still, some papers that only used radar or satellite images were also included.

Each of these AI paradigms has behaved differently in recent years. Although the use of AI has generally increased and expanded in the last decades, the number of neural network-related studies has increased significantly, while research involving fuzzy logic seems to be stagnant and has even decreased, with most studies appearing between 2013 and 2016 (Fig. 2). A summary of the main references is presented in Table I.

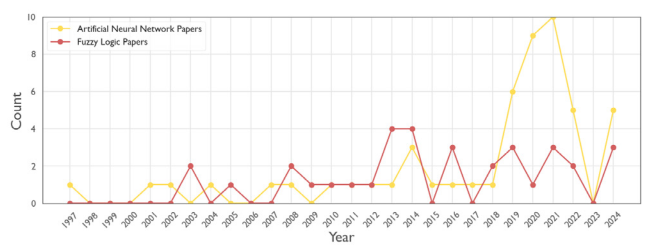

Figure 2. Number of papers by year and subject
Source: Authors

Neural networks for precipitation estimation

Artificial neural networks

ANNs, or simply *neural networks* (NNs), are connectionist models used to approximate a general function through a series of non-linear transformations performed by interconnected nodes or neurons [16]. ANNs are widely used in the field of machine learning, specifically in supervised learning with known input and output data (observations). During the initial training, iterative optimization algorithms are applied to slightly update the network in each iteration. This process runs until the known input data generate a very similar value to the known output data, which implies an optimal network configuration [17]. A well-trained NN can internally generalize the relationship between input and output, correctly approaching the objective function (*e.g.*, modeling the behavior of precipitation from historical data).

The simplest NN model is the multilayer perceptron (MLP), which has at least three layers: an input layer, a hidden layer, and an output layer (Fig. 3). Each node or perceptron is partially modeled as a biological neuron, wherein backpropagation is the usual training method. Thus, MLPs are also called *backpropagation neural networks* (BPNNs). In several studies, ANN, NN, and BPNN are used interchangeably, but it must be clarified that are differences in the in the configuration of the network and in internal parameters like the weights, the bias matrix, the transfer function, and the optimization algorithm [18]. [19] conducted a study aimed at identifying relationships between atmospheric temperature and rainfall with ANN models.

Different types of AI and machine learning models can be used for precipitation prediction and forecasting applications, such as expert systems, NNs, and deep learning. In the realm of deep learning, it is possible to find models like convolutional NNs, recurrent NNs, and generative adversarial networks. ANNs have been used to complete missing data in precipitation time series [20], as well as in autoregressive models, where precipitation is modeled from historical data, as was done by [21] for 15 min precipitation, by [22] for daily precipitation, by [23] for daily precipitation with wavelets analysis, and by [24] for monthly precipitation from rain gauge data between 1961 and 2018 in the Wujiang River Basin while using an artificial bee algorithm. Moreover, [25] performed a similar study in Greece. Simpler single-layer models like the ADALINE network have been used for monthly precipitation forecasting [26].

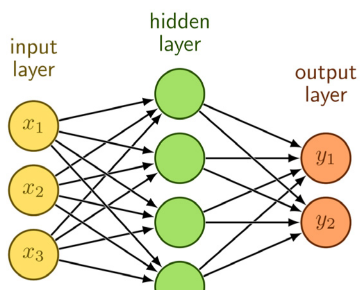

Figure 3. Neural network topology
Source: Adapted from [27]

Different input variables can be used besides precipitation. [28] included precipitable water vapor, pressure, temperature, relative humidity, cloud top temperature, cloud top pressure, and cloud top altitude to predict hourly precipitation. Other studies have used climate indices such as the southern oscillation index (SOI), the interdecadal pacific oscillation index (IPO), La Niña 3.4 [29], [30], and the standard precipitation index (SPI) [31] as input variables.

[32] used different types of NNs to estimate monthly mean precipitation and temperature based on data from 90 weather stations, with the purpose of elaborating a climatic cartography of Chile. Likewise, [33] delved into spatiotemporal predictions in Brazil. [34] used precipitation time series derived from stations monitoring data and radar and satellite images from different weather products, and [35] applied NNs to estimate precipitation using the WSR-88D radar in Oklahoma.

[36] were the first to describe the application of ANNs to satellite images in order to improve spatial precipitation estimation. Multiple products were derived from their studies, *e.g.*, the PERSIANN system. Furthermore, with the advent of new weather products, precipitation databases, and new research, new studies have mostly taken interest in integrating data from various sources [12]. [37] used data from satellite products (ERA-5, CHIRPS, IMD, PERSIANN-CDR) to create a machine learning algorithm that combined different sources to achieve what they called *secondary precipitation estimate merging using machine learning* (SPEM2L).

Since the target variable is precipitation, most papers seek to implement regressions. However, classification processes can also be applied, as was the case with [38], who used data from the global navigation satellite system (GNSS) to identify heavy precipitation.

Recurrent neural networks

Recurrent NNs are a special type of network whose neurons include an additional connection to themselves that works as a buffer or memory element (Fig. 4). This configuration is particularly useful to approximate relations depending on previous data such as time series [39]. There are different types: the basic recurrent neural network (RNN), the gated recurrent unit (GRU), and long short-term memory (LSTM).

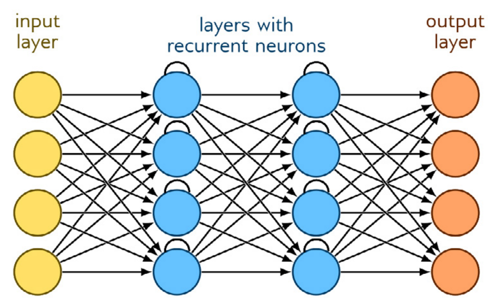

Figure 4. Recurrent neural network topology
Source: [40]

Deep and convolutional neural networks

Deep neural networks (DNNs) are a relatively new concept that involves ANNs containing many neurons, hidden layers, and training data. This kind of architecture has shown very good results in practice, especially with large amounts of quality data and high computational power available for training and validation [41]. The field of deep learning has gained ground for its great performance, to the point that the term *neural networks* is now directly associated with deep learning. [42] integrated data from different sources to predict precipitation using a deep network. Meanwhile, [43] implemented a classification model to identify heavy rain events, and [44] used bio-spectral images to predict precipitation.

The progress of DNNs also allowed developing new configurations like convolutional neural networks (CNNs). These networks use specialized nodes (Fig. 5) that work as sliding filters (*i.e.*, they convolute) on the input data to identify the particular characteristics that activate them [45]. This behavior is suitable for image analysis aimed at object detection, instance segmentation, and image and pixel classification [46]. In precipitation analysis, this can be applied in the detection of clouds, weather fronts, and atmospheric dynamics in radar products, *etc.*

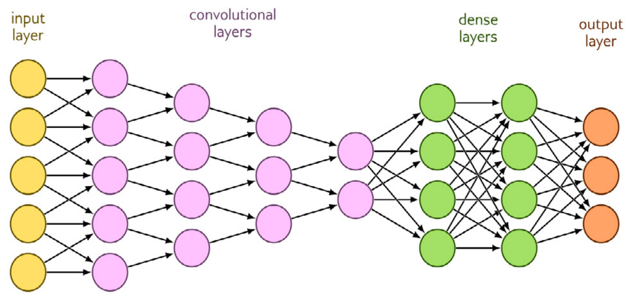

Figure 5. Convolutional neural network topology
Source: Adapted from [40]

[47] merged data from rain gauges, radar satellite images, and digital elevation models for precipitation estimation. They used CNNs and an additional post-processing step related to precipitation probability and intensity. The integration of radar data was improved, and the station bias was reduced in subsequent research [48]. Precipitation dynamics were analyzed in another study using both DNNs and CNNs applied to images obtained from terrestrial radars [49]. A CNN-based deep learning method was used to improve rainfall-runoff modeling in the Mekon River Basin [50]. One study explored the application of a CNN-based architecture for detecting and estimating near real-time precipitation in the USA [51].

In recent years, methods based on deep CNNs have achieved significant success, and their performance continues to improve [52]. [53] set about correcting the bias of daily satellite precipitation in tropical regions using a DNN. Most deep and convolutional models use non structured data as input (*e.g.*, images). A specific study on precipitation presented a nowcasting method based on sparse correspondence and a DNN [49]. The necessary data can be obtained directly from remote sensing products, generated from curated data provided by multiple sources, or generated from statistical or numerical models. For example, [54] used data from the ERA5 numerical and reanalysis model and the E-OBS database to apply a U-net (deep and convolutional network). The input data included weather and physical variable maps considering temperature, wind speed, water vapor, and geopotential altitude to generate the output, in the form of an hourly precipitation map.

Another project, focused on short-term weather forecasting (*i.e.*, nowcasting), mainly used CNNs or variants with recurrent components. Here, [55] used precipitation data from radar and satellite images provided by the Geostationary Satellite Server (GOES), together with physical weather models commonly used in meteorology. They obtained good results for 12 h forecasts. [56] applied a hybrid MLP and CNN model to predict extreme regional precipitation in central-eastern China. Similarly, [57] conducted a quantitative precipitation forecasting study for China with a multi-stream CNN. On the other hand, [58] applied CNNs in the United Kingdom. They added a generative component, wherein two modules (the generator and the discriminator) compete to generate an optimal output.

Optical flow can also be used on radar images [59] and in direct processing and detection from satellite images [60], [61]. Due to the sequential nature of precipitation data, it is possible to merge image and temporal analysis [62] using models that integrate convolutions and LSTM [63]. [64] proposed a transformer-enhanced spatiotemporal neural network called *TransLSTMUNet* for the post-processing of precipitation forecasts, and, using a DNN, [65] developed a forecasting model based on the global normalized difference vegetation index (NDVI), air temperature, soil moisture, and precipitation.

Thanks to the availability of precipitation data from satellite images, videos, and climate reanalysis products, a whole new wave of studies using computer vision has emerged. For instance, [66] compared several convolutional models (LSTM and U-Nets) for precipitation nowcasting within a 15 min temporal scale. Notably, a large volume of precipitation images was required.

Downscaling methods

The downscaling and regionalization of data allows improving the spatial scale of weather data or radar and optical images obtained via remote sensing in order to produce information that better captures the study area [11]. [67] applied downscaling with different machine learning models for precipitation estimation, using data from the Coupled Model Intercomparison Project Phase 5 (CMIP5). [68] and [69] used CNNs for the micro-regional monitoring of precipitation, while [70] analyzed the probability of extreme events through downscaling. [71] applied radial-basis NNs based on downscaling, integrating data from precipitation time series, global circulation models, and different climate change scenarios as inputs. Downscaling can be applied by means of different models (*e.g.*, statistical methods) or through classical NNs [72], CNNs, and U-nets [73]. Depending on the data available, this can be done on different temporal scales (annual, monthly, or daily) [74].

Fuzzy logic for precipitation estimation

Fuzzy inference systems

Fuzzy logic is based on the concept of *fuzzy sets*. A fuzzy set is a set with no crisp or clear boundary. Unlike two-valued Boolean logic, fuzzy logic is multi-valued, and it deals with degrees of membership and truth. Fuzzy logic uses any logical value from the set of real numbers between 0 (completely false) and 1 (completely true). This is known as the *membership value*, and the function that represents such value is called a *membership function* [75]. Fuzzy logic takes advantage of expert knowledge and the flexibility of fuzzy sets to model complex systems [18]. It allows representing numerical variables as identifiable linguistic values through membership functions (facilitating the representation of uncertainty and vagueness) (Fig. 6). Moreover, interpretable logic rules can be applied to these linguistic variables in the inference process. The fuzzy inference system (FIS) is the common configuration, comprising three main steps: fuzzification, inference, and defuzzification (Fig. 7).

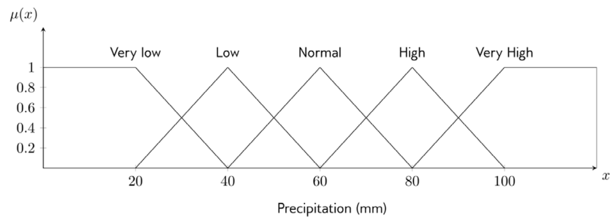

Figure 6. Example of a membership function
Source: Adapted from [76]

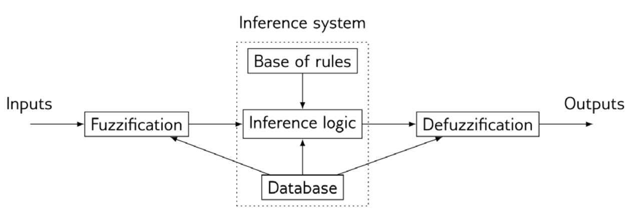

Figure 7. Fuzzy inference system
Source: Adapted from [77]

A special instance of this approach is the *Mamdani fuzzy inference system* (MFIS), which is widely accepted among the scientific community due to its interpretability. Here, the consequent of the implication rules is a single value. On the other hand, the Sugeno fuzzy inference system (SFIS) has a consequent with an arbitrary fuzzy function that considers all the variables in the antecedent [16]. The behavior of a FIS can be visualized, for two inputs and a single output, as a three-dimensional surface indicating the non-linear relation between the variables (Fig. 8) – when more variables are added, it generates an n-dimensional hyperplane [78].

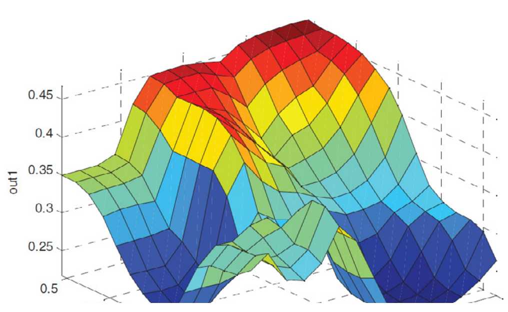

Figure 8. FIS output surface example for precipitation estimation from time series data
Source: [78]

[79] applied triangular membership functions to a FIS for precipitation data imputation. Precipitation prediction from other weather variables is also possible: [80] implemented a FIS using maximum, minimum, and mean values for wind speed, precipitation, and temperature as input in a model with 23 inference rules. [76] only used wind speed and air temperature. [81] applied fuzzy logic to a set of geographical variables including altitude, distance to the coastline, and slope – in addition to rain gauge data – to improve precipitation maps from meteorological radars.

[82] incorporated atmospheric pressure, humidity, dew point, temperature, and wind speed as input variables. The membership functions for each variable were triangular, with simple linguistic categories ranging from *very low* to *very high* in a MFIS. Furthermore, [83] added a temporal variable to differentiate the current day from the day before in their accumulated daily precipitation analysis. It is also possible to use preprocessed data such as those from the meteorological aerodrome report (METAR), a very common source in aerospace applications and weather analysis for air bases [84]; or those from the National Oceanic and Atmospheric Administration (NOAA) which offers data on different weather variables [85]. The main objective of the study by [84] was to predict rainfall events using a rule-based FIS that incorporated five parameters: relative humidity, total cloud cover, wind direction, temperature, and surface pressure. Similarly, [86] analyzed the uncertainties associated with extreme rainfall in terms of return levels. They also quantified the potential risk of these events in the coastal wetlands of India using fuzzy logic. [87] worked with fuzzy rainfall-runoff models to generate predictions for claypan catchments with conservation buffers in northeastern Missouri. Finally, [88] studied the climate sensitivity of mountainous regions to natural hazards through a fuzzy logic approach, identifying alterations in the level, intensity, or type of precipitation as the main drivers, together with glacier melting and permafrost thawing.

Fuzzy clustering and interpolation

Fuzzy systems can be implemented to improve the spatial interpolation of precipitation. [89] applied fuzzy logic to inverse distance weighting (IDW) for the spatial interpolation of precipitation, aiming to reduce the estimation error at river basin level. There are similar methods exclusively based on spatial interpolation [90] or classification, as is the case of [91], who used fuzzy logic to zone monthly precipitation and improve decision-making for cacao cultivation.

On the other hand, fuzzy clustering, or fuzzy C-means (FCM), is the use of membership functions to cluster, group, or categorize elements according to a similarity criterion. For example, [92] implemented this method to estimate precipitation and generate flood maps, and [90] applied it to validate spatial precipitation estimation. Fuzzy clustering can also be applied for downscaling precipitation data [93].

Fuzzy time series

Although FIS are mainly used for a system of inputs and outputs where the temporal component is not clearly incorporated, fuzzy logic can also be used for time series analysis. In this case, the time series should be interpreted as a fuzzy set. For example, [94] used fuzzy time series and NNs to predict rainfall, and, in complementary work, [78] focused exclusively on precipitation time series.

Within a purely autoregressive approach, membership functions are created by temporally dividing the precipitation time series [96]. In said cases, the membership functions split the data according to their temporal scale, *i.e.*, the linguistic variable can be the month of the year, and, after the fuzzification of the inputs, the inference rules can directly reference the known experimental behavior of the precipitation in certain months (Fig. 9).

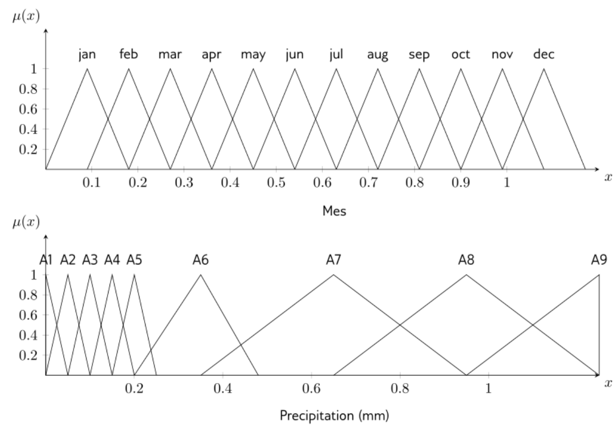

Figure 9. Membership functions for fuzzy time series
Source: Adapted from [97]

Hybrid models: neuro-fuzzy systems

Hybrid models refers to instances that integrate machine learning components to complement FIS, *e.g.*, NNs and genetic algorithms. Given the high effectiveness recently shown by machine learning applied to big data applications, it is increasingly common to include it as an additional step for expert systems. For example, NNs can be used to automatically generate membership functions for FIS, or even to generate inference rules [98]. [99] used NNs to generate inference rules within a so-called *neuro-fuzzy system* (NFS), using coordinates and their corresponding precipitation values, in a study similar to that by [100]. [101] merged data from stations, radar, and satellite images using a neuro-fuzzy network.

Another very common architecture in the literature corresponds to the adaptive neuro-fuzzy inference system (ANFIS) (Fig. 10). Neuro-fuzzy hybridization results in a hybrid intelligent system that synergizes ANNs and fuzzy logic by combining the human-inspired reasoning of fuzzy systems with the learning and connectionist structure of NNs [75]. [102] applied ANFIS to estimate precipitation from several rain gauge stations in Serbia, reporting improved reliability against uncertainty. Using ANFIS, [103] managed to identify the most relevant meteorological variables and their influence on precipitation estimation. They included data on vapor pressure, air temperature, the monthly frequency of wet days and the percent monthly cloud cover. Meanwhile, [104] used this approach to improve precipitation estimation from radar data. Some comparative studies have implemented the ANFIS method [23], as well as others focused on predicting precipitation-related climatic indices [105] or on using historical precipitation series.

Several models can also be merged into this approach, wherein the fuzzy logic component serves as a module integrator [106]. [107] presented a self-identification neuro-fuzzy inference model (SINFIM) for modeling the relationship between rainfall and runoff on a Chilean watershed. Another work studied the trends and patterns of rainfall to conduct an analysis of the city of Mumbai via the rainfall regionalization approach coupled with fuzzy logic and clustering [108]. [109] applied an ANFIS to evaluate rainfall-runoff modeling in a sub-catchment of the Kranji Basin in Singapore, and another study used NNs and fuzzy logic in statistical downscaling to support daily precipitation forecasting [110].

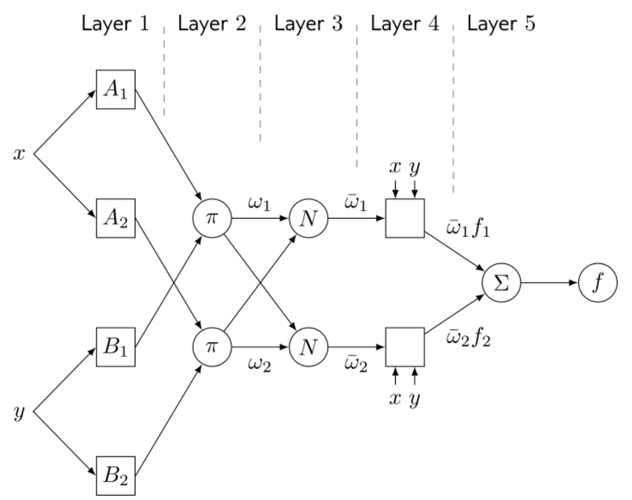

Figure 10. Topology of an ANFIS model
Source: Adapted from [103]

Hybrid metaheuristic algorithms

Hybrid metaheuristic algorithms are advanced tools in the field of AI [111]. These techniques can solve problems via prediction errors, hyperparameter determination, and feature selection using machine learning algorithms [112], which is why they are gaining popularity and are being used for the development of hybrid models for hydrological research [113], including those dealing with the prediction of reference evapotranspiration (ETo), a very important parameter for determining the availability of water resources and in hydrological studies. However, they are mainly used to predict ETo, as stated by [114]. To this effect, they studied and compared the prediction capabilities of two support vector regression (SVR) models along with three metaheuristic algorithms, *i.e.*, particle swarm optimization (PSO), gray wolf optimization (GWO), and the gravitational search algorithm (GSA), using meteorological variables in monthly ETo prediction used meteorological variables as input.

Hybrid metaheuristic algorithms have also been used to elaborate flood susceptibility maps, and the optimization capabilities offered by different machine learning algorithms has been leveraged by means of metaheuristic algorithms [111]. In the Haraz Basin, Iran, [115] employed an ANFIS coupled with the cropping (CA), bee (BA), and invasive weed optimization (IWO) algorithms. [116] used a combination of ANFIS, the genetic algorithm (GA), ant colony optimization (ACO), and PSO to generate a flood susceptibility map for the municipality of Jahrom, Iran. [24] performed ANFIS optimization with biogeography-based optimization (BBO) and the imperialist competitive algorithm (ICA). [117] used differential evolution (DE), the GA, and PSO along with an ANFIS to elaborate a flood susceptibility map for the Ganges Plain in India. [118] also used a combination of SVR, the GWO, and the bat optimizer (Bat) to generate this type of map. [119] used GWO and the whale optimization algorithm (WOA) to optimize SVR and create a flood susceptibility map for the Ardabil province in Iran. [120] combined SVR, PSO, and the grasshopper optimization algorithm (GOA) to develop a flood susceptibility map. [121] used the group method of data management (GMDH), DE, and the GA to generate a flood susceptibility map for the Haraz-Neka Basin, Iran. Moreover, [122] conducted GMDH optimization with the help of GWO in flood modeling.

[123] explored the accurate prediction of daily rainfall via AI methods. These methods were grounded in an ANFIS. Some metaheuristic optimization algorithms were also employed: the artificial bee colony algorithm (ABC), the GA, and simulated annealing (SA). [124] presented a method for providing explainability in the integration of inductive rules, combined with fuzzy logic and data mining techniques, when dealing with meteorological predictions.

Machine learning

Machine learning (ML) is a field of AI that deals with the development and study of statistical algorithms capable of learning from data and generalizing to unseen data, allowing them to perform tasks without explicit instructions.

In this vein, there are some studies related to precipitation forecasting and ML. [125] developed a conceptual metaheuristics-based framework for improving runoff time series simulation in glacierized catchments, combining hydrological model with a series predictor model and the optimization-driven parameter tuning of the firefly algorithm. Furthermore, [126] used a MLP network – optimized via the GA, PSO, the firefly algorithm, and teleconnection pattern indices – for rainfall modeling in the Mediterranean Basin. In addition, nested hybrid rainfall-runoff modelling has been performed via embedding ML techniques [127]. [128] used a combination of approaches, *i.e.*, statistical, ML, deep learning (DL), and hybrid algorithms, in order to build a precipitation forecasting system. In addition, [129] proposed a new rainfall prediction model that employs different techniques as well as indicator features like average directional movement (ADX), moving average convergence divergence (MACD), and Welles Wilder's smoothing average (WWS). [130] developed a metaheuristic evolutionary DL model based on a temporal convolutional network for rainfall-runoff simulation and multi-step runoff prediction. [131] assessed some rainfall prediction models to explore the advantages of ML and remote sensing approaches. Furthermore, an assessment of hybrid ML algorithms using TRMM rainfall data for daily inflow forecasting was carried out in eastern Brazil [132]. In China, a study on automated ML for rainfall-induced landslide hazard mapping was conducted [133]. [134] performed a comparative assessment of rainfall-based water level prediction methods using ML. [135] evaluated traditional and ML approaches to rainfall prediction, and [136] examined a combination of the ERA5 dataset and ML. Long-term rainfall prediction was performed by [137], using atmospheric synoptic patterns in semiarid climates with statistical and ML methods. [138] studied ML-based rainfall models for accurate flood mapping in Pakistan. [139] conducted specific studies on short-term rainfall forecasting using cumulative precipitation fields from station data with a probabilistic ML approach.

Comparative analysis

Input variables

Both NNs and fuzzy logic models depend on the available input variables. An initial knowledge of the objective function and the possible relationships between the explanatory and response variables is assumed in order to build the model. Fig. 11 shows the common input variables for the studied field. In general, these parameters can be classified as meteorological, physiographic, or hydrological variables; climatic indices; data derived from physical or numerical models; satellite or radar products; or other derived databases.

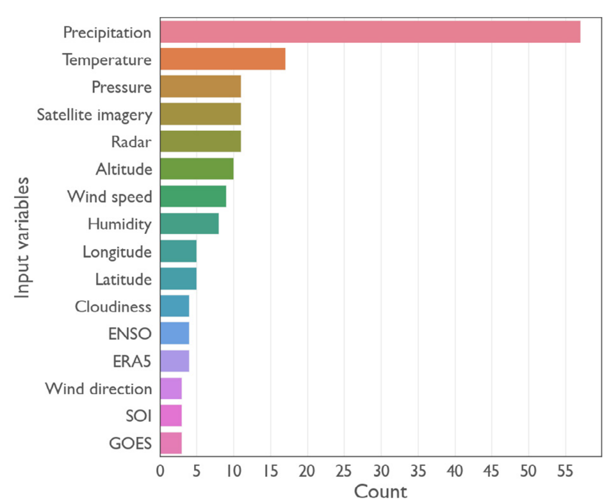

Figure 11. Input variables used in the references
Source: Authors

Output variables

As the purpose of these models is estimating it, precipitation should be the output or target variable in most cases. However, this variable can be expressed in diverse temporal scales, units, or configurations, as shown in Fig. 12. In some studies, both precipitation and temperature are included as output variables [32]. The most widely used output is monthly precipitation, mainly in the fields of weather forecasting and climate analysis. These variables also allow evaluating extreme events and return periods.

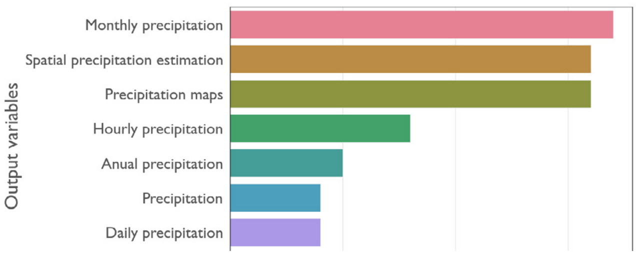

Figure 12. Output variables used in the references
Source: Authors

Model architectures

Fig. 13 shows the common NN architectures for precipitation estimation. ANNs and BPNN are differentiated as in the referenced literature. Although DNNs, CNNs, and convolutional-recurrent networks (CRNs) are shown separately, they could be grouped into a single category (*i.e.*, deep networks) that is representative of the selected references.

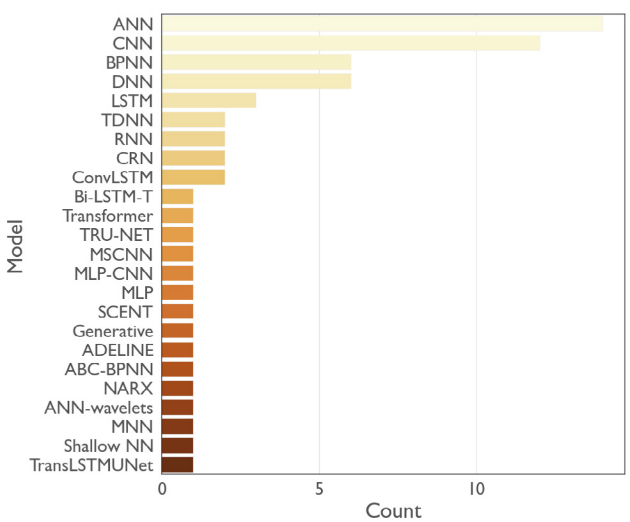

Figure 13. Neural network models found in the references
Source: Authors

Fig. 14 shows fuzzy logic models for precipitation estimation. ANFIS, FIS, and MFIS are the most commonly used. It could be said that MFIS are just a special case of FIS. On the other hand, both ANFIS and NFS integrate neural elements, so they represent the hybrid models in the references.

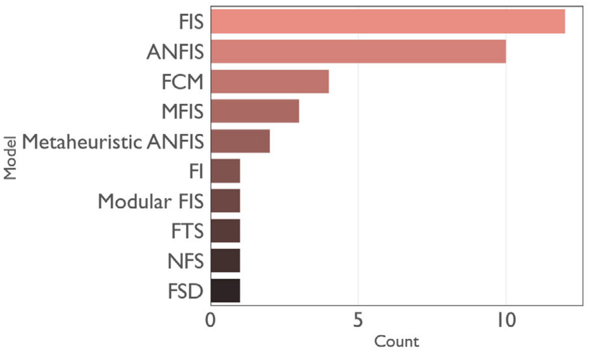

Figure 14. Fuzzy logic models found in the references
Source: Authors

Performance metrics

To validate the techniques discussed herein, it is necessary to use certain performance metrics or criteria in order to compare actual values to those generated by the models. Some of the most common metrics include the root mean square error (RMSE), the correlation coefficient (R), the determination coefficient (R^2), and the mean absolute error (MAE), which are mainly applied to regression models. In the case of classification models, performance evaluation should be mixed; for example, a confusion matrix can be used, as well as the F1 score or accuracy values. Among the performance metrics used in the referenced literature (Fig. 15), there are specific indicators for the field of hydrology, such as the average flood exposure risk (AFER), a specialized metric for flood analysis; Nash-Sutcliffe efficiency (NSE), widely employed in model assessment; the fractions skill score (FSS) for forecasting; and the skill score (SS) denominations, which are employed in quantitative precipitation forecasting (QPF). Apart from these, the RMSE, MAE, and R stand out as the most common parameters in fuzzy logic models implementing regression approaches.

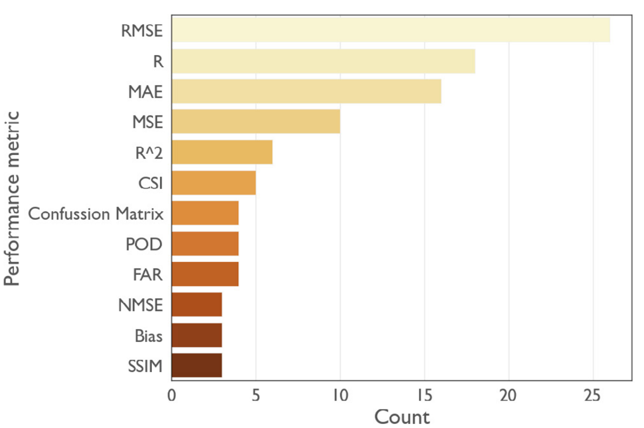

Figure 15. Neural network performance metrics
Source: Authors

Software tools and implementation

AI models can be implemented using different software tools and programming languages. A few references clearly describe the software used for implementation, but most of them do not provide clear information in this regard. The MATLAB software is notably used to implement of both NNs and fuzzy logic models [80]. In addition, the R language is applied for statistical analysis and downscaling [71], and some Python libraries are used for DL models [62]. It is important to highlight that the use of statistical software and geographical information systems is essential in this field.

Applications

For the general applications mentioned in the literature on precipitation estimation, some categories are identified. Firstly, as expected, precipitation forecasting on different temporal scales tends to be the main objective of several papers. For long-term temporal scales (30 years or more), the objective is climate analysis. Some papers emphasize the usefulness of AI techniques for issuing extreme event early warnings and in watershed management [21], [24], [78], [92].

Advantages and challenges of AI methodologies

AI methods exhibit both limitations and advantages. The fundamental aspects of the main methods are outlined below.

ML offers significant advantages regarding automation, accuracy, and scalability, but it poses challenges related to data dependence, model complexity, resource requirements, and ethical considerations. Fuzzy logic is quite advantageous in handling uncertainty, providing intuitive solutions and adaptability across various domains. However, its limitations are related to precision, rule design complexity, computational effort, and the lack of self-learning capabilities. Moreover, NNs are powerful and versatile tools capable of learning complex patterns from large datasets with good learning performance, adaptability, versatility, and the possibility of continuous improvement. However, they come with significant challenges related to data dependence, computational load, interpretability, and overfitting, all of which need to be carefully managed to ensure an effective and ethical use. NFS offer a powerful combination of the learning capabilities of NNs and the interpretability and uncertainty management of fuzzy logic. These hybrid models are particularly valuable in applications that require both adaptive learning and human-like reasoning. However, they pose challenges pertaining to complexity, computational effort, overfitting, and data quality dependence. Careful design and implementation are required to fully realize these techniques' potential while managing their limitations.

Conclusions

This work presents the results of a thorough review of the literature on prediction precipitation using AI techniques. Our findings provide academia and society in general with perspectives for future research in the field. There are various approaches for precipitation estimation using AI, even when limiting the search to two specific paradigms such as NNs and fuzzy logic. Model selection widely depends on the type, quantity, and quality of the available data, and there is no single configuration that guarantees the best results. The integration of multiple data sources holds great potential for performing regression in future studies.

Although the number of studies involving fuzzy logic has decreased, these models remain a relevant option due to their interpretability. Access to large amounts of data could benefit fuzzy logic, as achieved through the inclusion of ML components to create hybrid models, allowing for scaling while maintaining interpretability.

NN research applied to precipitation estimation has grown in recent years, with more sophisticated models like deep, recurrent, and convolutional networks being incorporated and showing significantly better results. However, among their limitations is the availability of and access to large amounts of data or high computational power, as well as the lack of interpretability and implementation issues.

There are still many challenges for precipitation estimation at the river basin level. Advances in the field of AI and access to new data sources, models, and software tools have yielded very promising results for the study of precipitation at different levels, from mere forecasting to extreme events forecasting and hydrological and environmental modeling.

CRediT author statement

All authors: conceptualization, methodology, software, validation, formal analysis, investigation, writing (original draft, review and editing), data curation, supervision. All authors contributed to the writing of the manuscript and approved its definitive version for publication.

Conflicts of interest

The authors declare no conflict of interest.

References

[1] UNESCO, Eds., *Informe mundial de las Naciones Unidas sobre el desarrollo de los recursos hídricos 2020: agua y cambio climático*. Paris, France: UNESCO, 2020. https://unesdoc.unesco.org/ark:/48223/pf0000372985_spa

[2] J. Wang, P. Zhai, and C. Li, "Non-uniform changes of daily precipitation in China: Observations and simulations," *Weather Clim. Ext.*, vol. 44, Article 100665, 2024. https://doi.org/10.1016/j.wace.2024.100665

[3] MAVDT, "Política nacional para la gestión integral del recurso hídrico," 2010. [Online]. Available: https://www.minambiente.gov.co/wp-content/uploads/2021/10/Politica-nacional-Gestion-integral-de-recurso-Hidrico-web.pdf?utm_source=chatgpt.com

[4] S. Zhu, Z. Xu, X. Luo, C. Wang, and J. Wu, "Assessing coincidence probability for extreme precipitation events in the Jinsha River basin," *Theor. Appl. Climatol.*, vol. 139, no. 1, pp. 825–835, Jan. 2020. https://doi.org/10.1007/s00704-019-03009-1

[5] R. Prudden *et al.*, "A review of radar-based nowcasting of precipitation and applicable machine learning techniques," 2020. [Online]. Available: https://arxiv.org/abs/2005.04988v1

[6] IPCC, Eds., *Climate change 2007: The physical science basis: Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge, UK; New York, NY, USA: Cambridge University Press, 2007. https://www.ipcc.ch/report/ar4/wg1/

[7] T. Davie, *Fundamentals of hydrology*, 3rd ed. London, UK; New York, NY, USA: Routledge, Taylor & Francis Group, 2019.

[8] B. Hingray, C. Picouet, A. Musy, and B. Hingray, *Hydrology: A science for engineers*. Boca Raton, FL, USA: CRC Press, Taylor & Francis Group, 2014.

[9] R. Buizza, "Chaos and weather prediction," 2002. [Online]. Available: https://www.ecmwf.int/node/16927

[10] D. S. Wilks, *Statistical methods in the atmospheric sciences*, 4th ed. Cambridge, UK: Elsevier, 2019.

[11] Q. Yuan *et al.*, "Deep learning in environmental remote sensing: Achievements and challenges," *Rem. Sens. Environ.*, vol. 241, art. 111716, May 2020. https://doi.org/10.1016/j.rse.2020.111716

[12] R. S. Khan and M. A. E. Bhuiyan, "Artificial intelligence-based techniques for rainfall estimation integrating multisource precipitation datasets," *Atmosphere*, vol. 12, no. 10, art. 10, Oct. 2021. https://doi.org/10.3390/atmos12101239

[13] Md. A. Saleh, H. M. Rasel, and B. Ray, "A comprehensive review towards resilient rainfall forecasting models using artificial intelligence techniques," *Green Tech. Sust.*, vol. 2, no. 3, art. 100104, Sep. 2024. https://doi.org/10.1016/j.grets.2024.100104

[14] A. Perianes-Rodriguez, L. Waltman, and N. J. van Eck, "Constructing bibliometric networks: A comparison between full and fractional counting," *J. Informetrics*, vol. 10, no. 4, pp. 1178–1195, Nov. 2016. https://doi.org/10.1016/j.joi.2016.10.006

[15] N. J. van Eck and L. Waltman, "VOSviewer Manual," 2021. [Online]. Available: https://www.vosviewer.com/getting-started

[16] K.-L. Du and M. N. S. Swamy, "Neural networks and statistical learning," 2019. [Online]. Available: https://doi.org/10.1007/978-1-4471-7452-3

[17] M. T. Hagan, H. B. Demuth, M. Hudson, and O. Jesús, "Neural network design," 2014. [Online]. Available: https://pdfs.semanticscholar.org/ee5d/5f138cb3220fbca642ec099d1bab9b41e410.pdf

[18] S. Russell and P. Norvig, *Artificial intelligence: A modern approach*, 3rd ed. Upper Saddle River, NJ, USA: Pearson, 2009.

[19] U. R. Anushka-Perera, "Rainfall and atmospheric temperature against the other climatic factors: A case study from Colombo, Sri Lanka," *Math. Prob. Eng.*, vol. 2019, art. 5692753, 2019. https://doi.org/10.1155/2019/5692753

[20] J. Kajornrit, K. W. Wong, and C. C. Fung, "Estimation of missing precipitation records using modular artificial neural networks," in *Int. Conf. Neural Info. Proc.*, 2012, pp. 52–59. [Online]. Available: https://link.springer.com/chapter/10.1007/978-3-642-34478-7_7

[21] K. C. Luk, J. E. Ball, and A. Sharma, "An application of artificial neural networks for rainfall forecasting," *Math. Comp. Model.*, vol. 33, no. 6, pp. 683–693, Mar. 2001. https://doi.org/10.1016/S0895-7177(00)00272-7

[22] W. Hong, "Rainfall forecasting by technological machine learning models," *App. Math. Comp.*, vol. 200, no. 1, pp. 41–57, Jun. 2008. https://doi.org/10.1016/j.amc.2007.10.046

[23] A. Solgi, V. Nourani, and A. Pourhaghi, "Forecasting daily precipitation using hybrid model of wavelet-artificial neural network and comparison with adaptive neuro-fuzzy inference system (case study: Verayneh Station, Nahavand)," *Adv. Civil Eng.*, vol. 2014, pp. 1–12, 2014. https://doi.org/10.1155/2014/279368

[24] Y. Wang, J. Liu, R. Li, X. Suo, and E. Lu, "Precipitation forecast of the Wujiang River Basin based on artificial bee colony algorithm and backpropagation neural network," *Alexandria Eng. J.*, vol. 59, no. 3, pp. 1473–1483, Jun. 2020. https://doi.org/10.1016/j.aej.2020.04.035

[25] K. P. Moustris, I. K. Larissi, P. T. Nastos, and A. G. Paliatsos, "Precipitation forecast using artificial neural networks in specific regions of Greece," *Water Res. Manag.*, vol. 25, no. 8, pp. 1979–1993, Jun. 2011. https://doi.org/10.1007/s11269-011-9790-5

[26] I. Sutawinaya, I. N. G. Astawa, and N. K. Hariyanti, "Comparison of adaline and multiple linear regression methods for rainfall forecasting," *J. Phys. Conf. Ser.*, vol. 953, pp. 1–8, Feb. 2018. https://doi.org/10.1088/1742-6596/953/1/012046

[27] S. Araghinejad, *Data-driven modeling: Using MATLAB® in water resources and environmental engineering*. Dordrecht, Netherlands: Springer, 2014. https:/doi.org/10.1007/978-94-007-7506-0

[28] P. Benevides, J. Catalao, and G. Nico, "Neural network approach to forecast hourly intense rainfall using GNSS precipitable water vapor and meteorological sensors," *Rem. Sens.*, vol. 11, no. 8, art. 8, Jan. 2019. https://doi.org/10.3390/rs11080966

[29] J. Abbot and J. Marohasy, "Input selection and optimisation for monthly rainfall forecasting in Queensland, Australia, using artificial neural networks," *Atmos. Res.*, vol. 138, pp. 166–178, Mar. 2014. https://doi.org/10.1016/j.atmosres.2013.11.002

[30] J. Abbot and J. Marohasy, "The application of artificial intelligence for monthly rainfall forecasting in the Brisbane Catchment, Queensland, Australia," *WIT Tran. Ecol. Environ.*, vol. 172, pp. 125–135, May 2013. https://doi.org/10.2495/RBM130111

[31] S. Azimi and M. Azhdary-Moghaddam, "Modeling short term rainfall forecast using neural networks, and Gaussian process classification based on the SPI drought index," *Water Res. Manag.*, vol. 34, no. 4, pp. 1369–1405, Mar. 2020. https://doi.org/10.1007/s11269-020-02507-6

[32] F. Neira, "Elaboración de la cartografía climática de temperaturas y precipitación mediante redes neuronales artificiales: caso de estudio en la Región del Libertador Bernardo O"Higgins," 2010, [Online]. Available: http://repositorio.uchile.cl/handle/2250/112354

[33] P. S. Lucio, F. C. Conde, I. F. A. Cavalcanti, A. I. Serrano, A. M. Ramos, and A. O. Cardoso, "Spatiotemporal monthly rainfall reconstruction via artificial neural network -case study: South of Brazil," *Adv. Geosci.*, vol. 10, pp. 67–76, 2007. https://doi.org/10.5194/adgeo-10-67-2007

[34] Y. Seo, S. Kim, and V. P. Singh, "Estimating spatial precipitation using regression kriging and artificial neural network residual kriging (RKNNRK) hybrid approach," *Water Res. Manag.*, vol. 29, no. 7, pp. 2189–2204, May 2015. https://doi.org/10.1007/s11269-015-0935-9

[35] T. B. Trafalis, M. B. Richman, A. White, and B. Santosa, "Data mining techniques for improved WSR-88D rainfall estimation," *Comp. Ind. Eng.*, vol. 43, no. 4, pp. 775–786, Sep. 2002. https://doi.org/10.1016/S0360-8352(02)00139-0

[36] K. L. Hsu, X. Gao, S. Sorooshian, and H. V. Gupta, "Precipitation estimation from remotely sensed information using artificial neural networks," *J. Appl. Meteorol.*, vol. 36, no. 9, pp. 1176–1190, Sep. 1997. https://doi.org/10.1175/1520-0450(1997)036<1176:PEFRSI>2.0.CO;2

[37] V. Kolluru, S. Kolluru, N. Wagle, and T. D. Acharya, "Secondary precipitation estimate merging using machine learning: Development and evaluation over Krishna River Basin, India," *Rem. Sens.*, vol. 12, no. 18, art. 18, Jan. 2020. https://doi.org/10.3390/rs12183013

[38] H. Li *et al.*, "A neural network-based approach for the detection of heavy precipitation using GNSS observations and surface meteorological data," *J. Atmos. Solar-Terres. Phys.*, vol. 225, art. 105763, Nov. 2021. https://doi.org/10.1016/j.jastp.2021.105763

[39] D. Z. Haq *et al.*, "Long short-term memory algorithm for rainfall prediction based on El-Nino and IOD data," *Proc. Comp. Sci.*, vol. 179, pp. 829–837, 2021. https://doi.org/10.1016/j.procs.2021.01.071

[40] A. Tch, "The mostly complete chart of neural networks, explained," Medium. [Online]. Available: https://towardsdatascience.com/the-mostly-complete-chart-of-neural-networks-explained-3fb6f2367464

[41] Y. Tao, X. Gao, A. Ihler, K. Hsu, and S. Sorooshian, "Deep neural networks for precipitation estimation from remotely sensed information," in *2016 IEEE Cong. Evol. Comp. (CEC)*, 2016, pp. 1349–1355. [Online]. Available: http://ieeexplore.ieee.org/abstract/document/7743945/

[42] H. G. Damavandi and R. Shah, "A learning framework for an accurate prediction of rainfall rates," 2019. [Online]. Available: http://arxiv.org/abs/1901.05885

[43] M. Sangiorgio *et al.*, "A comparative study on machine learning techniques for intense convective rainfall events forecasting," in *Theory and Applications of Time Series Analysis*, O. Valenzuela, F. Rojas, L. J. Herrera, H. Pomares, and I. Rojas, Eds. Cham, Germany: Springer International Publishing, 2020, pp. 305–317.

[44] Y. Tao, X. Gao, A. Ihler, S. Sorooshian, and K. Hsu, "Precipitation identification with bispectral satellite information using deep learning approaches," *J. Hydrometeorol.*, vol. 18, no. 5, pp. 1271–1283, May 2017. https://doi.org/10.1175/JHM-D-16-0176.1

[45] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, art. 7553, May 2015. https://doi.org/10.1038/nature14539

[46] X. X. Zhu *et al.*, "Deep learning in remote sensing: A comprehensive review and list of resources," *IEEE Geosci. Rem. Sens. Mag.*, vol. 5, no. 4, pp. 8–36, Dec. 2017. https://doi.org/10.1109/MGRS.2017.2762307

[47] A. Moraux, S. Dewitte, B. Cornelis, and A. Munteanu, "Deep learning for precipitation estimation from satellite and rain gauges measurements," *Rem. Sens.*, vol. 11, no. 21, art. 21, Jan. 2019. https://doi.org/10.3390/rs11212463

[48] A. Moraux, S. Dewitte, B. Cornelis, and A. Munteanu, "A deep learning multimodal method for precipitation estimation," *Rem. Sens.*, vol. 13, no. 16, art. 16, Jan. 2021. https://doi.org/10.3390/rs13163278

[49] W. Fang, F. Zhang, V. S. Sheng, and Y. Ding, "SCENT: A new precipitation nowcasting method based on sparse correspondence and deep neural network," *Neurocomputing*, art. S0925231221003283, Mar. 2021. https://doi.org/10.1016/j.neucom.2021.02.072

[50] X.-H. Le, Y. Kim, D.-V. Binh, S. Jung, and D.-H. Nguyen, "Improving rainfall-runoff modeling in the Mekon river basin using bias-correct satellite precipitation products by convolutional neural networks," *J. Hydrol.*, vol. 630, art. 130762, 2024. https://doi.org/10.1016/j.jhydrol.2024.130762

[51] M. Sadeghi, P. Nguyen, K. Hsu, and S. Sorooshian, "Improving near real-time precipitation estimation using a U-Net convolutional neural network and geographical information," *Environ. Model. Soft.*, vol. 134, art. 104856, Dec. 2020. https://doi.org/10.1016/j.envsoft.2020.104856

[52] J. Wang, L. Lin, Z. Zhang, S. Gao, and H. Yu, "Deep neural network based on dynamic attention and layer attention for meteorological data downscaling," *ISPRS J. Photogramm. Rem. Sens.*, vol. 215, pp. 157–176, Sep. 2024. https://doi.org/10.1016/j.isprsjprs.2024.06.020

[53] X. Yang *et al.*, "Correcting the bias of daily satellite precipitation estimates in tropical regions using deep neural network," *J. Hydrol.*, art. 608 127656, 2022. https://doi.org/10.1016/j.jhydrol.2022.127656

[54] R. Adewoyin, P. Dueben, P. A. G. Watson, Y. He, and R. Dutta, "TRU-NET: A deep learning approach to high resolution prediction of rainfall," 2020. [Online]. Available: https://research-information.bris.ac.uk/en/publications/tru-net-a-deep-learning-approach-to-high-resolution-prediction-of

[55] L. Espeholt *et al.*, "Skillful twelve hour precipitation forecasts using large context neural networks," 2021. [Online]. Available: http://arxiv.org/abs/2111.07470

[56] Q. Jiang, F. Cioffi, W. Li, J. Tan, X. Pan, and X. Li, "Hybrid multilayer perceptron and convolutional neural network model to predict extreme regional precipitation dominated by the large-scale atmospheric circulation," *Atmos. Res.*, vol. 304, art. 107362, 2024. https://doi.org/10.1016/j.atmosres.2024.107362

[57] Y. Tian, Y. Ji, X. Gao, X. Yuan, and X. Zhi, "Post-processing of short-term quantitative precipitation forecast with the multi-stream convolutional neural network," *Atmos. Res.*, vol. 309, art. 107584, Oct. 2024. https://doi.org/10.1016/j.atmosres.2024.107584

[58] S. Ravuri *et al.*, "Skilful precipitation nowcasting using deep generative models of radar," *Nature*, vol. 597, no. 7878, pp. 672–677, Sep. 2021. https://doi.org/10.1038/s41586-021-03854-z

[59] S. Agrawal, L. Barrington, C. Bromberg, J. Burge, C. Gazen, and J. Hickey, "Machine learning for precipitation nowcasting from radar images," 2019. [Online]. Available: https://doi.org/10.48550/arXiv.1912.12132

[60] V. A. Gorooh, A. A. Asanjan, P. Nguyen, K. Hsu, and S. Sorooshian, "Deep neural network high spatiotemporal resolution precipitation estimation (Deep-STEP) using passive microwave and infrared data," *J. Hydrometeorol.*, vol. 23, no. 4, pp. 597–617, Apr. 2022. https://doi.org/10.1175/JHM-D-21-0194.1

[61] W. Li, B. Pan, J. Xia, and Q. Duan, "Convolutional neural network-based statistical post-processing of ensemble precipitation forecasts," *J. Hydrol.*, vol. 605, art. 127301, Feb. 2022. https://doi.org/10.1016/j.jhydrol.2021.127301

[62] X. Shi *et al.*, "Deep learning for precipitation nowcasting: A benchmark and a new model," *NeurIPS*, vol. 30, art. 11, 2017. https://doi.org/10.48550/arXiv.1706.03458

[63] C. K. Sønderby *et al.*, "MetNet: A neural weather model for precipitation forecasting," 2020. [Online]. Available: https://arxiv.org/abs/2003.12140

[64] M. Jiang, B. Weng, J. Chen, T. Huang, F. Ye, and L. You, "Transformer-enhanced spatiotemporal neural network for post-processing of precipitation forecasts," *J. Hydrol.*, vol. 630, art. 130720, 2024. https://doi.org/10.1016/j.jhydrol.2024.130720

[65] L. Fathollahi, F. Wu, R. Melaki, P. Jamshidi, and S. Sarwar, "Global normalized difference vegetation index forecasting from air temperature, soil moisture and precipitation using a deep neural network," *App. Comp. Geosci.*, vol. 23, art. 100174, 2024. https://doi.org/10.1016/j.acags.2024.100174

[66] M. C. Bakkay *et al.*, "Precipitaion nowcasting using deep neural network," 2022. [Online]. Available: http://arxiv.org/abs/2203.13263

[67] R. Xu, N. Chen, Y. Chen, and Z. Chen, "Downscaling and projection of multi-CMIP5 precipitation using machine learning methods in the Upper Han River Basin," *Adv. Meteorol.*, vol. 2020, pp. 1–17, Mar. 2020. https://doi.org/10.1155/2020/8680436

[68] X. Shi, "Enabling smart dynamical downscaling of extreme precipitation events with machine learning," *Geophys. Res. Lett.*, vol. 47, no. 19, Oct. 2020. https://doi.org/10.1029/2020GL090309

[69] B. Kumar, R. Chattopadhyay, M. Singh, N. Chaudhari, K. Kodari, and A. Barve, "Deep-learning based down-scaling of summer monsoon rainfall data over Indian region," 2020. [Online]. Available: http://arxiv.org/abs/2011.11313

[70] H. Hu and B. M. Ayyub, "Machine learning for projecting extreme precipitation intensity for short durations in a changing climate," *Geosciences*, vol. 9, no. 5, art. 209, May 2019. https://doi.org/10.3390/geosciences9050209

[71] D. D. Montenegro Murillo, M. A. Pérez Ortiz, and V. Vargas Franco, "Predicción de precipitación mensual mediante redes neuronales artificiales para la cuenca del río Cali, Colombia," *DYNA*, vol. 86, no. 211, pp. 122–130, Oct. 2019. https://doi.org/10.15446/dyna.v86n211.76079

[72] T. Trinh, N. Do, V. T. Nguyen, and K. Carr, "Modeling high-resolution precipitation by coupling a regional climate model with a machine learning model: an application to Sai Gon–Dong Nai Rivers Basin in Vietnam," *Clim. Dyn.*, vol. 57, no. 9, pp. 2713–2735, Nov. 2021. https://doi.org/10.1007/s00382-021-05833-6

[73] A. Y. Sun and G. Tang, "Downscaling satellite and reanalysis precipitation products using attention-based deep convolutional neural nets," *Front. Water*, vol. 2, art. 536743, 2020. [Online]. Available: https://www.frontiersin.org/article/10.3389/frwa.2020.536743

[74] B. Pan, K. Hsu, A. AghaKouchak, and S. Sorooshian, "Improving precipitation estimation using convolutional neural network," *Water Resour. Res.*, vol. 55, no. 3, pp. 2301–2321, Mar. 2019. https://doi.org/10.1029/2018WR024090

[75] A. Talei, L. H. C. Chua, and C. Quek, "A novel application of a neuro-fuzzy computational technique in event-based rain-fall–runoff modeling," *Exp. Sys. App.*, vol. 37, pp. 7456–7468, 2010. https://doi.org/10.[1016/j.eswa.2010.04.015

[76] M. A. Rahman, "Improvement of rainfall prediction model by using fuzzy logic," *Am. J. Clim. Change*, vol. 9, no. 4, art. 4, Nov. 2020. https://doi.org/10.4236/ajcc.2020.94024

[77] A. Sözen, M. Kurt, M. A. Akçayol, and M. Özalp, "Performance prediction of a solar driven ejector-absorption cycle using fuzzy logic," *Renew. Energy*, vol. 29, no. 1, pp. 53–71, Jan. 2004. https://doi.org/10.1016/S0960-1481(03)00172-1

[78] J. Kaiornrit, K. W. Wong, and C. C. Fung, "A modular technique for monthly rainfall time series prediction," in *2013 IEEE Symp. Comp. Intel. Dyn. Uncert. Environ. (CIDUE)*, 2013, pp. 76–83. https://doi.org/10.1109/CIDUE.2013.6595775

[79] C. Tzimopoulo, L. Mpallas, and C. Evangelide, "Fuzzy model comparison to extrapolate rainfall data," *J. Environ. Sci. Tech.*, vol. 1, no. 4, pp. 214–224, Sep. 2008. https://doi.org/10.3923/jest.2008.214.224

[80] R. Janarthanan, R. Balamurali, A. Annapoorani, and V. Vimala, "Prediction of rainfall using fuzzy logic," *Mater. Today Proc.*, vol. 37, pp. 959–963, 2021. https://doi.org/10.1016/j.matpr.2020.06.179

[81] M. Silver, T. Svoray, A. Karnieli, and E. Fred, "Improving weather radar precipitation maps: A fuzzy logic approach," *Atmos. Res.*, vol. 234, art. 104710, Oct. 2019. https://doi.org/10.1016/j.atmosres.2019.104710

[82] A. Helen, A. Gabriel, A. E., and B. Alese, "Development of a fuzzy logic based rainfall prediction model," *Int. J. Eng. Tech.*, vol. 3, pp. 427–435, Jan. 2013. https://www.researchgate.net/publication/285799840_Development_of_a_fuzzy_logic_based_rainfall_prediction_model

[83] M. Hasan, T. Tsegaye, X. Shi, G. Schaefer, and G. Taylor, "Model for predicting rainfall by fuzzy set theory using USDA scan data," *Agri. Water Manag.*, vol. 95, no. 12, pp. 1350–1360, Dec. 2008. https://doi.org/10.1016/j.agwat.2008.07.015

[84] S. Asklany, K. Elhelow, I. Youssef, and M. El-Wahab, "Rainfall events prediction using rule-based fuzzy inference system," *Atmos. Res.*, vol. 101, pp. 228–236, Jul. 2011. https://doi.org/10.1016/j.atmosres.2011.02.015

[85] G. Abbas Fall, M. Mousavi-Ba, and M. Habibi Nok, "Annual rainfall forecasting by using mamdani fuzzy inference system," *Res. J. Environ. Sci.*, vol. 3, no. 4, pp. 400–413, Apr. 2009. https://doi.org/10.3923/rjes.2009.400.413

[86] S. Rakkasagi, M. K. Goyal, and S. Jha, "Evaluating the future risk of coastal Ramsar wetlands in India to extreme rainfalls using fuzzy logic," *J. Hydrol.*, vol. 632, art. 130869, 2024. https://doi.org/10.1016/j.jhydrol.2024.130869

[87] G. M. M. M. A. Senaviratne, R. P. Udawatta, S. H. Anderson, C. Baf-faut, and A. Thompson, "Use of fuzzy rainfall–runoff predictions for claypan watersheds with conservation buffers in Northeast Missouri," *J. Hydrol.*, vol. 517, pp. 1008–1018, 2014. https://doi.org/10.1016/j.jhydrol.2014.06.023

[88] P. Mani, S. Allen, S. Kotlarski, and M. Stoffel, "Climate sensitivity of natural hazards processes in mountain regions: A fuzzy logic approach," *Geomorphology*, vol. 461, art. 109329, 2024. https://doi.org/10.1016/j.geomorph.2024.109329

[89] C. L. Chang, S. L. Lo, and S. L. Yu, "Applying fuzzy theory and genetic algorithm to interpolate precipitation," *J. Hydrol.*, vol. 314, no. 1, pp. 92–104, Nov. 2005. https://doi.org/10.1016/j.jhydrol.2005.03.034

[90] J. Kajornrit and K. W. Wong, "Cluster validation methods for localization of spatial rainfall data in the northeast region of Thailand," in *2013 Int. Conf. Mach. Learn. Cyber.*, 2013, pp. 1637–1642. https://doi.org/10.1109/ICMLC.2013.6890861

[91] L. B. Franco, C. D. G. C. de Almeida, M. M. Freire, G. B. Franco, and S. de A. Silva, "Rainfall zoning for cocoa growing in Bahia state (Brazil) using fuzzy logic," *Eng. Agríc.*, vol. 39, special no., pp. 48–55, Sep. 2019. https://doi.org/10.1590/1809-4430-eng.agric.v39nep48-55/2019

[92] M. Zare, G. J.-P. Schumann, F. N. Teferle, and R. Mansorian, "Generating flood hazard maps based on an innovative spatial interpolation methodology for precipitation," *Atmosphere*, vol. 12, no. 10, art. 10, Oct. 2021. https://doi.org/10.3390/atmos12101336

[93] P. Sinha *et al.*, "Downscaled rainfall projections in south Florida using self-organizing maps," *Sci. Total Environ.*, vol. 635, pp. 1110–1123, Sep. 2018. https://doi.org/10.1016/j.scitotenv.2018.04.144

[94] P. Singh, "Rainfall and financial forecasting using fuzzy time series and neural networks based model," *Int. J. Mach. Learn. Cyber.*, vol. 9, no. 3, pp. 491–506, Mar. 2018. https://doi.org/10.1007/s13042-016-0548-5

[95] J. Kajornrit, K. W. Wong, and C. C. Fung, "Rainfall prediction in the northeast region of Thailand using Modular Fuzzy Inference System," in *2012 IEEE Int. Conf. Fuzzy Syst.*, 2012, pp. 1–6. https://doi.org/10.1109/FUZZ-IEEE.2012.6250785

[96] S. Dani and S. Sharma, "Forecasting rainfall of a region by using fuzzy time series," *Asian J. Math. App.*, vol. 2013, 2013. https://scienceasia.asia/files/65.pdf

[97] J. Kajornrit, "Interpretable fuzzy systems for monthly rainfall spatial interpolation and time series prediction," PhD dissertation, Murdoch Univ., Perth, Australia, 2014. [Online]. Available: https://researchrepository.murdoch.edu.au/id/eprint/26220/

[98] J.-S. R. Jang, "ANFIS: adaptive-network-based fuzzy inference system," *IEEE Trans. Syst. Man. Cyber.*, no. 3, art. 665, 1993. https://doi.org/10.1109/21.256541

[99] K. W. Wong, P. M. Wong, T. D. Gedeon, and C. C. Fung, "Rainfall prediction model using soft computing technique," *Soft Comp.*, vol. 7, no. 6, pp. 434–438, May 2003. https://doi.org/10.1007/s00500-002-0232-4

[100] P. V. de Campos Souza, L. Batista de Oliveira, and L. A. Ferreira do Nascimento, "Fuzzy rules to help predict rains and temperatures in a Brazilian capital state based on data collected from satellites," *App. Sci.*, vol. 9, no. 24, art. 5476, Dec. 2019. https://doi.org/10.3390/app9245476

[101] F. Chang, Y.-M. Chiang, M.-J. Tsai, M.-C. Shieh, K.-L. Hsu, and S. Sorooshian, "Watershed rainfall forecasting using neuro-fuzzy networks with the assimilation of multi-sensor information," *J. Hydrol.*, vol. 508, pp. 374–384, Jan. 2014. https://doi.org/10.1016/j.jhydrol.2013.11.011

[102] D. Petković, M. Gocić, and S. Shamshirband, "Adaptive neuro-fuzzy computing technique for precipitation estimation," *Facta Univ. Ser. Mech. Eng.*, vol. 14, no. 2, pp. 209–218, 2016. https://doi.org/10.22190/FUME1602209P

[103] R. Hashim *et al.*, "Selection of meteorological parameters affecting rainfall estimation using neuro-fuzzy computing methodology," *Atmos. Res.*, vol. 171, supp. C, pp. 21–30, May 2016. https://doi.org/10.1016/j.atmosres.2015.12.002

[104] M. Hessami, F. Anctil, and A. A. Viau, "An adaptive neuro-fuzzy inference system for the post-calibration of weather radar rainfall estimation," *J. Hydroinfo.*, vol. 5, no. 1, pp. 63–70, Jan. 2003. https://doi.org/10.2166/hydro.2003.0005

[105] S. Sharma, P. Srivastava, X. Fang, and L. Kalin, "Hydrologic simulation approach for El Niño Southern Oscillation (ENSO)-affected watershed with limited raingauge stations," *Hydrol. Sci. J.*, vol. 61, no. 6, pp. 991–1000, Apr. 2016. https://doi.org/10.1080/02626667.2014.952640

[106] A. Rahman *et al.*, “Rainfall prediction system using machine learning fusion for smart cities,” *Sensors*, vol. 22, pp. 1–14, May 2022. https://doi.org/10.3390/s22093504

[107] Y. Morales, M. Querales, H. Rosas, H. Allende-Cid, and R. Salas, “A self-identification Neuro-Fuzzy inference framework for modeling rainfall-runoff in a Chilean watershed,” *J. Hydrol.,* vol. 23, art 125910, Aug. 2020. https://doi.org/10.1016/j.jhydrol.2020.125910

[108] Shahfahad, M. W. Naikoo, S. Talukdar, T. Das, and A. Rahman, “Identification of homogenous rainfall regions with trend analysis using fuzzy logic and clustering approach coupled with advanced trend analysis techniques in Mumbai city,” *Urb. Clim.*, vol. 46, art. 101306, Dec. 2022. https://doi.org/10.1016/j.uclim.2022.101306

[109] A. Talei, L. H. C. Ghua, and T. S. W. Wong, “Evaluation of rainfall and discharge inputs used by adaptive network-based fuzzy inference systems (ANFIS) in rainfall-runoff modeling,” *J. Hydrol.*, vol. 391, no. 3-4, pp. 248–262, 2010. https://doi.org/10.1016/j.jhydrol.2010.07.023

[110] M. C. Valverde, E. Araujo, and H. Campos Velho, “Neural network and fuzzy logic statistical downscaling of atmospheric circulation-type specific weather pattern for rainfall forecasting,” *App. Soft Comp.*, vol. 22, pp. 681–694, 2014. https://doi.org/10.1016/j.asoc.2014.02.025

[111] S. Askar *et al.*, “Flood susceptibility mapping using remote sensing and integration of decision table classifier and metaheuristic algorithms,” *Water*, vol. 14, no. 19, art. 3062, 2022. https://doi.org/10.3390/w14193062

[112] N.-D. Hoang and X.-L. Tran, “Remote sensing–based urban green space detection using marine predators algorithm optimized machine learning approach,” *Math. Probl. Eng*, art. 5586913, 2021. https://doi.org/10.1155/2021/5586913

[113] H. E. Khairan, S. L. Zubaidi, S. F. Raza, M. Hameed, N. Al-Ansari, and H. M. Ridha, “Examination of Single- and hybrid-based metaheuristic algorithms in ANN reference evapotranspiration estimating,” *Sustainability*, vol. 15, art. 14222, 2023. https://doi.org/10.3390/su151914222

[114] R. Adnan *et al.*, “Advanced hybrid metaheuristic machine learning models application for reference crop evapotranspiration prediction,” *Agronomy*, vol. 13, art. 98 10 3390 13010098, 2022. https://doi.org/10.3390/agronomy13010098

[115] D. T. Bui *et al.*, “Novel hybrid evolutionary algorithms for spatial prediction of floods,” *Sci. Rep.*, vol. 8, p. 15364, 2018. https://doi.org/10.1038/s41598-018-33620-1

[116] S. V. R. Termeh, A. Kornejady, H. R. Pourghasemi, and S. Keesstra, “Flood susceptibility mapping using novel ensembles of adaptive neuro fuzzy inference system and metaheuristic algorithms,” *Sci. Total Environ.*, vol. 615, pp. 438–451, 2018. https://doi.org/10.1016/j.scitotenv.2017.09.262Get rights and content

[117] A. Arora *et al.*, “Optimization of state-of-the-art fuzzy-metaheuristic anfis-based machine learning models for flood susceptibility prediction mapping in the middle Ganga plain, India,” *Sci. Total Environ.*, vol. 750, art. 141565, 2021. https://doi.org/10.1016/j.scitotenv.2020.141565

[118] O. Rahmati *et al.*, “Development of novel hybridized models for urban flood susceptibility mapping,” *Sci. Rep.*, vol. 10, art. 12937, 2020. https://doi.org/10.1038/s41598-020-69703-7

[119] F. Rezaie, M. Panahi, S. M. Bateni, C. Jun, C. M. Neale, and S. Lee, “Novel hybrid models by coupling support vector regression (SVR) with meta-heuristic algorithms (WOA and GWO) for flood susceptibility mapping,” *Nat. Haz.*, pp. 1–37, 2022. https://doi.org/10.1007/s11069-022-05424-6

[120] M. Panahi *et al.*, “Flood spatial prediction modeling using a hybrid of meta-optimization and support vector regression modeling,” *Catena*, vol. 199, art. 105114, 2021. https://doi.org/10.1016/j.catena.2020.105114

[121] E. Dodangeh *et al.*, “Novel hybrid intelligence models for flood-susceptibility prediction: Meta optimization of the GMDH and SVR models with the genetic algorithm and harmony search,” *J. Hydrol.*, vol. 590, art. 125423, 2020. https://doi.org/10.1016/j.jhydrol.2020.125423

[122] F. Rezaie, S. M. Bateni, E. Heggy, and S. Lee, “Utilizing the SAR, GIS, and novel hybrid metaheuristic-GMDH algorithm for flood susceptibility mapping,” in *Proc. 2021 IEEE Int. Geosci. Rem. Sens. Symp. IGARSS*, 2021, pp. 11-16. https://doi.org/10.1109/IGARSS47720.2021.9553468

[123] B. T. Pham, K.-T. T. Bui, I. Prakash, and B.-B. Ly, “Hybrid artificial intelligence models based on adaptive neuro fuzzy inference system and metaheuristic optimization algorithms for prediction of daily rainfall,” *Phys. Chem. Earth*, vol. 134, art. 103563, 2024. https://doi.org/10.1016/j.pce.2024.103563

[124] C. Peláez-Rodríguez *et al.*, “A general explicable forecasting framework for weather events based on ordinal classification and inductive rules combined with fuzzy logic,” *Knowledge-Based Syst.*, vol. 291, art. 111556, 2024. https://doi.org/10.1016/j.knosys.2024.111556

[125] B. Mohammadi, S. Vazifehkhah, and Z. Duan, “A conceptual metaheuristic-based framework for improving runoff time series simulation in glacierized catchments,” *Eng. App. Art. Intel.*, vol. 127, art. 107302, Jan. 2024. https://doi.org/10.1016/j.engappai.2023.107302

[126] B. Zerouali *et al.*, “Artificial intelligent systems optimized by metaheuristic algorithms and teleconnection indices for rainfall modeling: The case of a humid region in the mediterranean basin,” *Heliyon*, vol. 9, no. 4, art. e15355, Apr. 2023. https://doi.org/10.1016/j.heliyon.2023.e15355

[127] U. Okkan, Z. B. Ersoy, A. A. Kumanlioglu, and O. Fistikoglu, “Embedding machine learning techniques into a conceptual model to improve monthly runoff simulation: A nested hybrid rainfall runoff modeling,”. *J. Hydrol.*, vol. 598, art. 126433, 2021. https://doi.org/10.1016/j.jhydrol.2020.125423

[128] S. E. Priestly, K. Raimond, Y. Cohen, J. Brema, and D. J. Hemanth, “Evaluation of a novel hybrid lion swarm optimization – AdaBoostRegressor model for forecasting monthly precipitation,” *Sust. Comp. Info. Syst.*, vol. 39, art. 100884, 2023. https://doi.org/10.1016/j.suscom.2023.100884

[129] T. Anuradha, P. S. G. Aruna Sri Formal, and J. RamaDevi, "Hybrid model for rainfall prediction with statistical and technical indicator feature set," *Exp. Syst. App.*, vol. 249, art. 123260, Sep. 2024. https://doi.org/10.1016/j.eswa.2024.123260

[130] X. Qiao *et al.*, "Metaheuristic evolutionary deep learning model based on temporal convolutional network, improved aquila optimizer and random forest for rainfall-runoff simulation and multi-step runoff prediction," *Exp. Syst. App.*, vol. 229, art. 120616, Nov. 2023. https://doi.org/10.1016/j.eswa.2023.120616

[131] S. D. Latif *et al.*, "Assessing rainfall prediction models: Exploring the advantages of machine learning and remote sensing approaches," *Alexandria Eng. J.*, vol. 82, pp. 16–25, Nov. 2023. https://doi.org/10.1016/j.aej.2023.09.060

[132] E. Gomaa *et al.*, "Assessment of hybrid machine learning algorithms using TRMM rainfall data for daily inflow forecasting in Três Marias Reservoir, eastern Brazil," *Heliyon*, vol. 9, no. 8, art. e18819, Aug. 2023. https://doi.org/10.1016/j.heliyon.2023.e18819

[133] T. Li, C. Xie, C. Xu, W. Qi, Y. Huang, and L. Li, "Automated machine learning for rainfall-induced landslide hazard mapping in Luhe County of Guangdong Province, China," *China Geol.*, vol. 7, art. 315 329, 2024. https://doi.org/10.31035/cg2024064

[134] A. I. Pathan *et al.*, "Comparative assessment of rainfall-based water level prediction using machine learning (ML) techniques," *Ain Shams Eng. J.*, vol. 15, art. 102854, 2024. https://doi.org/10.1016/j.asej.2024.102854

[135] Y. Yin, J. He, J. Guo, W. Song, H. Zheng, and J. Dan, "Enhancing precipitation estimation accuracy: An evaluation of traditional and machine learning approaches in rainfall predictions," *J. Atmos. Solar-Terres. Phys*, vol. 255, art. 106175, Feb. 2024. https://doi.org/10.1016/j.jastp.2024.106175

[136] W. Dai *et al.*, "Estimation of rainfall erosivity on the Chinese Loess Plateau: A new combination of the ERA5 dataset and machine learning," *J. Hydrol.*, vol. 624, art. 129892, Sep. 2023. https://doi.org/10.1016/j.jhydrol.2023.129892

[137] J. Diez-Sierra and M. Del Jesus, "Long-term rainfall prediction using atmospheric synoptic patterns in semi-arid climates with statistical and machine learning methods," *J. Hydrol.*, vol. 586, art. 124789, Jul. 2020. https://doi.org/10.1016/j.jhydrol.2020.124789

[138] U. Rasool *et al.*, "Rainfall-driven machine learning models for accurate flood inundation mapping in Karachi, Pakistan," *Urb. Clim.*, vol. 49, art. 101573, May 2023. https://doi.org/10.1016/j.uclim.2023.101573

[139] D. Pirone, L. Cimorelli, G. Del Giudice, and D. Pianese, "Short-term rainfall forecasting using cumulative precipitation fields from station data: A probabilistic machine learning approach," *J. Hydrol.*, vol. 617, art. 128949, Feb. 2023. https://doi.org/10.1016/j.jhydrol.2022.128949

Table I. Main references by year and category regarding artificial neural networks and fuzzy logic-based approaches
Source: Authors

Title	Authors	Year	Country	Category	AI Model
Precipitation estimation from remotely sensed information using artificial neural networks	Hsu *et al.*	1997	USA	Artificial Neural Networks	ANN
An application of artificial neural networks for rainfall forecasting	Luk *et al.*	2001	Australia	Artificial Neural Networks	BPNN, RNN, TDNN
Data mining techniques for improved WSR-88D rainfall estimation	Trafalis *et al.*	2002	USA	Artificial Neural Networks	ANN
Precipitation estimation from remotely sensed imagery using an Artificial Neural Network Cloud Classification System	Hong *et al.*	2004	USA	Artificial Neural Networks	ANN
Spatiotemporal monthly rainfall reconstruction via artificial neural network -case study: south of Brazil	Lucio *et al.*	2007	Brazil	Artificial Neural Networks	ANN
Rainfall forecasting by technological machine learning models	W. Hong	2008	Taiwan	Artificial Neural Networks	RNN
Elaboración de la cartografía climática de temperaturas y precipitación mediante redes neuronales artificiales: caso de estudio en la Región del Libertador Bernardo O"Higgins	Román & Andrés	2010	Chile	Artificial Neural Networks	BPNN
Precipitation forecast using artificial neural networks in specific regions of Greece	Moustris *et al.*	2011	Greece	Artificial Neural Networks	ANN
Estimation of missing precipitation records using modular artificial neural networks	Kajornrit *et al.*	2012	Thailand	Artificial Neural Networks	BPNN, MNN
The application of artificial intelligence for monthly rainfall forecasting in the Brisbane Catchment, Queensland, Australia	Abbot and Marohasy	2013	Australia	Artificial Neural Networks	ANN
Artificial neural networks modeling for forecasting the maximum daily total precipitation at Athens, Greece	Nastos *et al.*	2014	Greece	Artificial Neural Networks	TDNN
Forecasting daily precipitation using hybrid model of wavelet-artificial neural network and comparison with adaptive neurofuzzy inference system (case study: Verayneh Station, Nahavand)	Solgi	2014	Iran	Artificial Neural Networks	ANN-wavelets
Input selection and optimisation for monthly rainfall forecasting in Queensland, Australia, using artificial neural networks	Abbot and Marohasy	2014	Australia	Artificial Neural Networks	ANN
Estimating spatial precipitation using regression kriging and artificial neural network residual kriging (RKNNRK) hybrid approach	Seo *et al.*	2015	South Korea	Artificial Neural Networks	ANN
Artificial neural networks in precipitation nowcasting: An Australian case study	Schroeter	2016	Australia	Artificial Neural Networks	Shallow NN
Precipitation identification with bispectral satellite information using deep learning approaches	Tao *et al.*	2017	USA	Artificial Neural Networks	DNN
Comparison of adaline and multiple linear regression methods for rainfall forecasting	Sutawinaya *et al.*	2018	Indonesia	Artificial Neural Networks	ADELINE
A learning framework for an accurate prediction of rainfall rates	Damavandi and Shah	2019	China, India, Pakistan	Artificial Neural Networks	BPNN

Deep learning for precipitation estimation from satellite and rain gauges measurements	Moraux *et al.*	2019	Germany, Belgium, Netherlands	Artificial Neural Networks	DNN, CNN
Neural network approach to forecast hourly intense rainfall using GNSS precipitable water vapor and meteorological sensors	Benevides *et al.*	2019	Portugal	Artificial Neural Networks	NARX
Predicción de precipitación mensual mediante redes neuronales artificiales para la cuenca del río Cali, Colombia	Montenegro Murillo *et al.*	2019	Colombia	Artificial Neural Networks	ANN
Improving precipitation estimation using convolutional neural network	Pan *et al.*	2019	USA	Artificial Neural Networks	CNN
Rainfall and atmospheric temperature against the other climatic factors: A case study from Colombo, Sri Lanka	Anushka-Perera	2019	Sri Lanka	Artificial Neural Networks	ANN
Modeling short term rainfall forecast using neural networks, and Gaussian process classification based on the SPI drought index	Azimi and Azhdary-Moghaddam	2020	Iran	Artificial Neural Networks	BPNN
Precipitation forecast of the Wujiang River Basin based on artificial bee colony algorithm and backpropagation neural network	Wang *et al.*	2020	China	Artificial Neural Networks	ABC-BPNN
Secondary precipitation estimate merging using machine learning: Development and evaluation over Krishna River Basin, India	Kolluru *et al.*	2020	India	Artificial Neural Networks	ANN
A comparative study on machine learning techniques for intense convective rainfall events forecasting	Sangiorgio *et al.*	2020	Italy	Artificial Neural Networks	DNN
Deep multilayer perceptron for knowledge extraction: Understanding the Gardon de Mialet flash floods modeling	Saint Fleur *et al.*	2020	France	Artificial Neural Networks	ANN
Downscaling satellite and reanalysis precipitation products using attention-based deep convolutional neural nets	Sun and Tang	2020	USA	Artificial Neural Networks	CNN
MetNet: A neural weather model for precipitation forecasting	Sønderby *et al.*	2020	USA	Artificial Neural Networks	ConvLSTM
Improving near real-time precipitation estimation using a U-Net convolutional neural network and geographical information	Sadegui *et al.*	2020	USA	Artificial Neural Networks	CNN
Artificial intelligence-based techniques for rainfall estimation integrating multisource precipitation datasets	Khan and Bhuiyan	2021	Ethiopia	Artificial Neural Networks	ANN
Long short-term memory algorithm for rainfall prediction based on El-Niño and IOD data	Haq *et al.*	2021	Indonesia	Artificial Neural Networks	LSTM
SCENT: A new precipitation nowcasting method based on sparse correspondence and deep neural network	Fang *et al.*	2021	China	Artificial Neural Networks	DNN,CNN
Skilful precipitation nowcasting using deep generative models of radar	Ravuri *et al.*	2021	United Kingdom	Artificial Neural Networks	Generativo
Skillful twelve hour precipitation forecasts using large context neural networks	Espeholt *et al.*	2021	USA	Artificial Neural Networks	CRN
TRU-NET: A deep learning approach to high resolution prediction of rainfall	Adewoyin *et al.*	2021	United Kingdom	Artificial Neural Networks	CRN
Modeling high-resolution precipitation by coupling a regional climate model with a machine learning model: an application to Sai Gon-Dong Nai Rivers Basin in Vietnam	Trinh *et al.*	2021	Vietnam	Artificial Neural Networks	ANN
A deep learning multimodal method for precipitation estimation	Moraux *et al.*	2021	Germany, Belgium, Netherlands	Artificial Neural Networks	DNN, CNN

A neural network-based approach for the detection of heavy precipitation using GNSS observations and surface meteorological data	Li *et al.*	2021	China	Artificial Neural Networks	BPNN
SCENT: A new precipitation nowcasting method based on sparse correspondence and deep neural network	Fang *et al.*	2021	China	Artificial Neural Networks	SCENT
Precipitaion nowcasting using deep neural network	Bakkay *et al.*	2022	France	Artificial Neural Networks	CNN, LSTM
Extreme precipitation prediction based on neural network model – A case study for southeastern Brazil	de Sousa Araújo *et al.*	2022	Brazil	Artificial Neural Networks	LSTM
Convolutional neural network-based statistical post-processing of ensemble precipitation forecasts	Li *et al.*	2022	China	Artificial Neural Networks	CNN
Deep neural network high spatiotemporal resolution precipitation estimation (Deep-STEP) using passive microwave and infrared data	Gorooh *et al.*	2022	USA	Artificial Neural Networks	CNN
Correcting the bias of daily satellite precipitation estimates in tropical regions using deep neural network	Yang *et al.*	2022	China	Artificial Neural Networks	Bi-LSTM-T
Hybrid multilayer perceptron and convolutional neural network model to predict extreme regional precipitation dominated by the large-scale atmospheric circulation	Jiang *et al.*	2024	China	Artificial Neural Networks	MLP, CNN, MLP-CNN
Post-processing of short-term quantitative precipitation forecast with the multi-stream convolutional neural network	Tian *et al.*	2024	China	Artificial Neural Networks	CNN, MSCNN
Transformer-enhanced spatiotemporal neural network for post-processing of precipitation forecasts	Jiang *et al.*	2024	China	Artificial Neural Networks	Transformer, TransLSTMUNet, ConvLSTM
Improving rainfall-runoff modeling in the Mekon river basin using bias-correct satellite precipitation products by convolutional neural networks	Le *et al.*	2024	China, Burma, Laos, Thailand, Cambodia, Vietnam	Artificial Neural Networks	CNN
Deep neural network based on dynamic attention and layer attention for meteorological data downscaling	Wang *et al.*	2024	China	Artificial Neural Networks	DNN
Rainfall prediction model using soft computing technique	Wong *et al.*	2003	Italy	Fuzzy Logic	NFS
An adaptive neuro-fuzzy inference system for the post-calibration of weather radar rainfall estimation	Hessami *et al.*	2003	Canada	Fuzzy Logic	ANFIS
Applying fuzzy theory and genetic algorithm to interpolate precipitation	Chang et al	2005	Taiwan	Fuzzy Logic	FI
Fuzzy model comparison to extrapolate rainfall data	Tzimopoulo *et al.*	2008	Greece	Fuzzy Logic	ANFIS
Model for predicting rainfall by fuzzy set theory using USDA scan data	Hasan *et al.*	2008	USA	Fuzzy Logic	FIS
Annual rainfall forecasting by using mamdani fuzzy inference system	Abbas *et al.*	2009	Iran	Fuzzy Logic	MFIS
Evaluation of rainfall and discharge inputs used by adaptive network-based fuzzy inference systems (ANFIS) in rainfall-runoff modeling	Talei *et al.*	2010	Singapore	Fuzzy Logic	ANFIS
Rainfall events prediction using rule-based fuzzy inference system	Asklany *et al.*	2011	Egypt	Fuzzy Logic	FIS
Rainfall prediction in the northeast region of Thailand using modular fuzzy inference system	Kajornrit *et al.*	2012	Thailand	Fuzzy Logic	FIS
A modular technique for monthly rainfall time series prediction	Kaiornrit *et al.*	2013	Thailand	Fuzzy Logic	MFIS
Cluster validation methods for localization of spatial rainfall data in the northeast region of Thailand	Kajornrit and Wong	2013	Thailand	Fuzzy Logic	FCM
Development of a fuzzy logic based rainfall prediction model	Helen *et al.*	2013	Nigeria	Fuzzy Logic	MFIS

Forecasting rainfall of a region by using fuzzy time series	(Dani & Sharma	2013		Fuzzy Logic	FIS
An integrated intelligent technique for monthly rainfall time series prediction	Kajornrit *et al.*	2014	Thailand	Fuzzy Logic	ANFIS
Interpretable fuzzy systems for monthly rainfall spatial interpolation and time series prediction	Kajornrit	2014	Thailand	Fuzzy Logic	FIS, ANFIS, Modular FIS
Watershed rainfall forecasting using neuro-fuzzy networks with the assimilation of multi-sensor information	F. Chang *et al.*	2014	Taiwan	Fuzzy Logic	ANFIS
Neural network and fuzzy logic statistical downscaling of atmospheric circulation-type specific weather pattern for rainfall forecasting	Valverde *et al.*	2014	Brazil	Fuzzy Logic	FSD
Adaptive neuro-fuzzy computing technique for precipitation estimation	Petković *et al.*	2016	Serbia	Fuzzy Logic	ANFIS
Hydrologic simulation approach for El Niño Southern Oscillation (ENSO)-affected watershed with limited raingauge stations	Sharma *et al.*	2016	USA	Fuzzy Logic	ANFIS
Selection of meteorological parameters affecting rainfall estimation using neuro-fuzzy computing methodology	Hashim *et al.*	2016	India	Fuzzy Logic	ANFIS
Rainfall and financial forecasting using fuzzy time series and neural networks based model	Singh	2018	India	Fuzzy Logic	FTS
Downscaled rainfall projections in south Florida using self-organizing maps	Sinha *et al.*	2018	USA	Fuzzy Logic	FCM
Fuzzy rules to help predict rains and temperatures in a brazilian capital state based on data collected from satellites	de Campos Souza *et al.*	2019	Brazil	Fuzzy Logic	ANFIS
Improving weather radar precipitation maps: A fuzzy logic approach	Silver *et al.*	2019	Israel	Fuzzy Logic	FIS
Rainfall zoning for cocoa growing in Bahia state (Brazil) using fuzzy logic	Franco *et al.*	2019	Brazil	Fuzzy Logic	FIS
Improvement of rainfall prediction model by using fuzzy logic	Rahman	2020	Bangladesh	Fuzzy Logic	FIS
Generating flood hazard maps based on an innovative spatial interpolation methodology for precipitation	Zare *et al.*	2021	Luxembourg, Germany, France	Fuzzy Logic	FCM
Prediction of rainfall using fuzzy logic	Janarthanan *et al.*	2021	India	Fuzzy Logic	FIS
Optimization of state-of-the-art fuzzy-metaheuristic ANFIS-based machine learning models for flood susceptibility prediction mapping in the middle Ganga Plain, India	Arora *et al.*	2021	India	Fuzzy Logic	Metaheuristic ANFIS
Rainfall prediction system using machine learning fusion for smart cities	Rahman *et al.*	2022	Pakistan	Fuzzy Logic	FIS
Identification of homogenous rainfall regions with trend analysis using fuzzy logic and clustering approach coupled with advanced trend analysis techniques in Mumbai city	Shahfahad *et al.*	2022	India	Fuzzy Logic	FCM
A general explicable forecasting framework for weather events based on ordinal classification and inductive rules combined with fuzzy logic	Peláez-Rodríguez *et al.*	2024	Spain	Fuzzy Logic	FIS
Hybrid artificial intelligence models based on adaptive neuro fuzzy inference system and metaheuristic optimization algorithms for prediction of daily rainfall	Pham *et al.*	2024	Vietnam	Fuzzy Logic	Metaheuristic ANFIS
Evaluating the future risk of coastal Ramsar wetlands in India to extreme rainfalls using fuzzy logic	Rakkasagi *et al.*	2024	India	Fuzzy Logic	FIS