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Review

Assessing rainfall prediction models: Exploring the advantages of machine learning and remote sensing approaches

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ABSTRACT

Using a comparison of three different major types, the best predictive model was determined. Statistical models and machine learning algorithms automatically learn and improve based on data. Deep learning uses neural networks to learn complex data patterns and relationships. A combination of satellite imagery, radar data, and ground-based observations are used and using aircraft or satellites, and remote sensing (RS) collects data on distant objects or locations. Satellites and radar are used to gather regional precipitation data for hybrid models. An algorithm trained on historical rainfall measurements would then process the data. Using remote monitoring instrument input features, the machine-learning model can predict precipitation. Evaluation of machine learning regression methods is based on the degree of agreement between predicted and observed values. The RMSE, R^2, and MAE statistical measures check on the precision of a prediction or forecasting model. Machine learning excels at rainfall prediction regardless of climate or timescale. As one of the more popular models for predicting rainfall, the LSTM models demonstrate their superiority. Remote sensing and hybrid predictive models should be investigated further due to their scarcity.

1. Introduction

The term “rainfall prediction” refers to the process of using various methods to predict the amount, timing, and location of precipitation (rain, snow, sleet, etc.) in a given area over a given period of time. Predicting when and how much rain will fall is a crucial aspect of weather forecasting that can benefit a variety of fields, including agriculture, transportation, water resource management, energy production disaster management and emergency response. Precipitation forecasts can be supported by conventional ground-based measurements, remote sensing, and numerical weather models. Rainfall is typically measured using rain gauges on the ground, but remote sensing can estimate rainfall using satellites and radar. Numerical weather models use mathematical equations to simulate atmospheric conditions and predict future weather patterns [1–4].

Rainfall forecasting is critical because heavy and irregular rainfall can have many consequences, such as crop destruction and property damage, so a better forecasting model is required for early warning that can minimize risks to life and property while also better managing agricultural farms. This prediction primarily benefits farmers, and water resources may be used more efficiently. Rainfall forecast is a difficult undertaking, and the findings must be precise. There are numerous hardware devices available for predicting rainfall based on weather parameters such as temperature, humidity, and pressure. Because traditional approaches are inefficient, we can achieve accurate results by employing machine learning algorithms. We can simply achieve that

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by analysing previous rainfall data and forecasting rainfall for future seasons. We can apply numerous techniques, such as classification and regression, depending on the requirements, and we can also calculate the error between the real and predicted values, as well as the accuracy. Because different methodologies provide varying degrees of accuracy, it is critical to select the appropriate algorithm and model it in accordance with the requirements [5,6].

Farmers rely on precipitation forecasts to schedule crop planting, fertilisation, and harvesting, as well as make decisions regarding irrigation. Accurate rainfall forecasting can aid farmers in preventing crop loss due to drought or flooding, optimising yields, and decreasing water consumption. In the agriculture sector, accurate prediction of rainfall is vital which can help in preventing damaging the crops by predicting the intense rainfall. Similar importance of the reliable prediction of rainfall can be found in other areas, especially in preventing flooding and assisting the early warning system. Rainfall forecasting has traditionally relied on physical models and statistical techniques to make predictions about future precipitation levels. With the introduction of machine learning and deep learning techniques, it is now possible to utilise these potent tools to increase the precision and dependability of precipitation forecasts [7,8].

Predicting rainfall is essential for water resource management, including the operation of reservoirs and dams, as well as water supply and distribution planning. With accurate rainfall prediction, water supply decision-makers can make more informed decisions regarding water allocation, release, and conservation. Accurate rainfall forecasting is essential for mitigating the effects of natural disasters like floods, landslides, and droughts. By allowing communities to prepare and respond appropriately, early warning systems based on precipitation forecasts can help reduce loss of life and property damage [9,10]. Accurate rainfall predictions can help transportation planners make informed decisions regarding the construction, maintenance, and safety of roads and bridges. It can also aid in the prevention of weather-related accidents and delays. Hydroelectric power generation is extremely reliant on precise precipitation forecasts, as they are vital for the scheduling and supervision of energy output. Rainfall also influences the planning and maintenance of other forms of energy production, such as solar and wind power, because it can affect their efficacy. Prediction of rainfall is essential for sustainable development, disaster risk reduction, and community welfare. It is essential in a variety of industries, and accurate and timely forecasting can help reduce economic losses, protect the environment, and improve living conditions [11,12].

However, erroneous rainfall forecasts can negatively impact many elements of civilization, such as agriculture, emergency management, and infrastructure development. Those who rely on weather forecasts should be made aware of any possible information gaps, and efforts are being made to improve forecast reliability.

In this review paper, various previous and recent studies for predicting rainfall utilizing machine learning and remote sensing approaches were reviewed and analysed in order to explore the novelty and advantages of those predicted models.

2. Methodology

This inquiry began with a search for, acquisition of, and analysis of literature on articles about forecasting rainfall. The search was conducted using Scopus, one of the most prominent databases for scientific research. Only publications classified as "articles" or "book chapters" were chosen for this investigation. A number of review publications addressed the use of machine learning models for rainfall prediction. However, no one has yet thoroughly compared remote sensing models to machine learning models.

An analysis of related experiments identifies the search equation as the new and most significant equation for rainfall prediction. The Scopus and IEEE database is used to keep the research up to date. The final search spans the years 2010 to 2023. Following a database search shown in Fig. 1, 1904 papers were found on Scopus and 206 papers found on IEEE. When combined, 1588 papers are rejected out as it does not relate to the topic at hand. Then another 452 papers are excluded due to the presence of duplicates, lack of accessibility and the papers are not niche to rainfall prediction using predictive models. An analysis was carried out after reviewing relevant articles. According to the following criteria, a number of articles were selected based on certain measures:

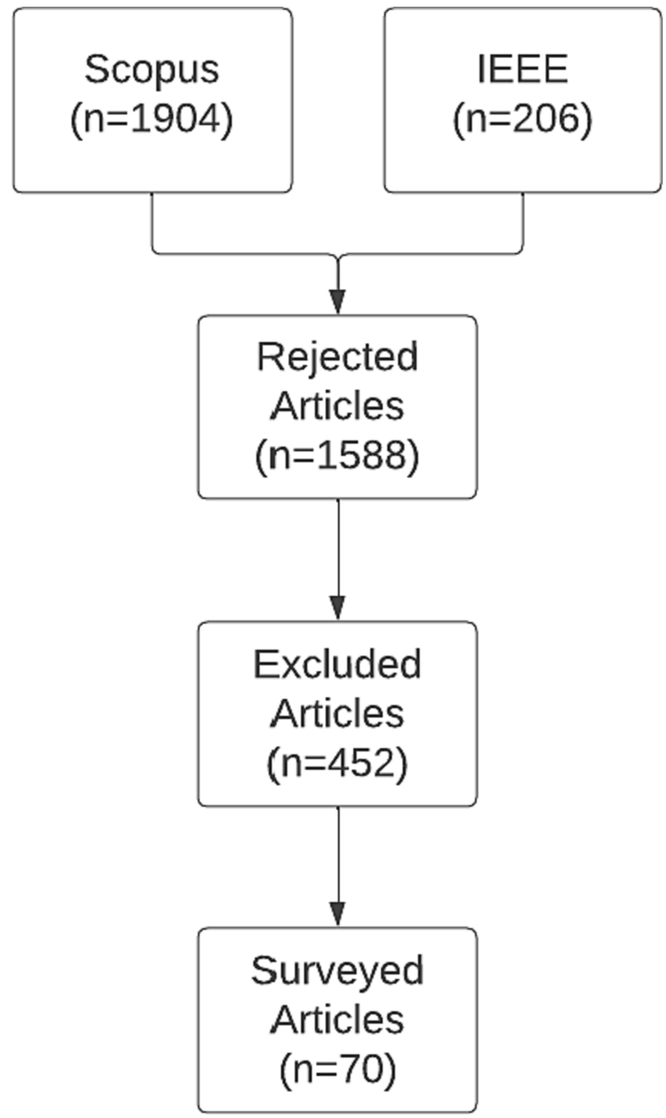

Fig. 1. Article selection process.

1. The study focuses mostly on rainfall predictions.
2. The investigation provides evaluation metrics.
3. The study provides predictions for variables.

Certain sets of related keywords were included in the search requests:

Set 1: "Rainfall"; Set 2: "forecasting", "prediction", "modelling", "machine learning", and "remote sensing". The AND operator was used between keywords in sets 1 and 2, while the OR operator was used between keywords within the sets.

The papers reviewed were published in 51 different journals. The ranking and number of papers selected from each journal are displayed in Table 1. IEEE Transactions on Geoscience has the greatest number of papers with 4 articles. This is followed by, IEEE Access, Water (Switzerland), International Journal of Advanced Computer Science and

Table 1
Research work of rainfall prediction.

Authors	Case Study	Initial Year	End Year	Type
[13]	Australia	2008	2017	Meteorological
[14]	India	2002	2022	Meteorological
[15]	China	2018	2019	Meteorological
[16]	Indonesia	1981	2020	Meteorological
[17]	India	1988	2021	Meteorological
[18]	India	2010	2014	Meteorological, Hydrological
[19]	India	1901	2016	Hydrological
[20]	Thailand	2004	2018	Meteorological, Hydrological
[21]	Nigeria	1991	2020	Hydrological
[22]	Nigeria	1974	2013	Hydrological
[2]	India	2015	2020	Hydrological
[23]	China	2006	2021	Meteorological, Hydrological
[24]	Australia	1960	2015	Hydrological
[9]	Korea	2018	2020	Hydrological
[25]	Singapore and Brazil	2010	2016	Meteorological
[26]	USA	2007	2008	Meteorological
[27]	USA	2004	2006	Meteorological
[28]	India	1991	2015	Hydrological
[29]	Ghana	1980	2019	Meteorological, Hydrological
[30]	India	1941	2005	Meteorological, Hydrological
[31]	India	1948	2020	Meteorological
[32]	Saudi Arabia	2019	2021	Hydrological
[33]	USA	1982	2015	Meteorological
[34]	Nigeria	1983	2013	Meteorological
[35]	USA	1980	2014	Meteorological, Hydrological
[36]	India	2012	2017	Meteorological
[37]	Taiwan	2021	2021	Hydrological
[1]	Pakistan	2005	2017	Hydrological
[38]	India	2012	2017	Meteorological, Hydrological
[39]	China	1999	2016	Hydrological
[40]	Australia	2012	2022	Meteorological
[41]	Ethiopia	1985	2017	Meteorological
[42]	Germany	1998	2014	Meteorological, Hydrological
[43]	China	1961	2019	Hydrological
[44]	Bangladesh	2012	2018	Hydrological
[45]	India	–	–	Meteorological, Hydrological
[46]	Indonesia	1982	2018	Hydrological
[47]	India	2012	2017	Meteorological
[48]	China	1981	2020	Hydrological
[49]	Saudi Arabia	–	–	Hydrological
[50]	Taiwan	1988	2020	Hydrological
[51]	India	1901	2020	Hydrological
[52]	Australia	1990	2012	Hydrological
[53]	China	1958	2016	Hydrological
[54]	United Kingdom	1979	2019	Meteorological
[55]	Taiwan	2013	2019	Meteorological, Hydrological
[56]	Ecuador	1981	2018	Meteorological
[57]	Saudi Arabia	1978	2016	Hydrological
[58]	India	1901	2019	Hydrological
[59]	China	–	–	Meteorological
[60]	Indonesia	2009	2018	Hydrological
[61]	Australia	1961	2017	Hydrological
[62]	Jordan	1938	2018	Hydrological
[63]	Iran	2003	2006	Meteorological
[64]	Indonesia	2009	2014	Meteorological, Hydrological
[65]	Bhutan	1997	2017	Meteorological
[66]	Indonesia	1994	2013	Hydrological
[67]	Indonesia	–	–	Hydrological
[68]	China	2014	2016	Hydrological
[69]	Brazil	1986	2015	Hydrological
[70]	India	1989	1995	Meteorological
[71]	Malaysia	1988	2017	Meteorological
[72]	Malaysia	2010	2015	Meteorological, Hydrological
[73]	China	2016	2016	Meteorological, Hydrological
[74]	Ecuador	1964	2015	Hydrological
[75]	Indonesia	2021	2021	Meteorological
[76]	Pakistan	2005	2017	Meteorological
[77]	Taiwan	2002	2014	Meteorological, Hydrological
[78]	India	1980	2014	Meteorological
[79]	India	1871	2012	Hydrological

Applications, and Atmosphere with 3 articles each. Then 5 journals, the Water Supply, Water, Sensors, Revue d'Intelligence Artificielle, Remote Sensing, Hydrology, and Computers, Materials and Continua has 2 articles each mentioned in this study. Each of the remaining journals has one article that has been included.

The majority of the publications are taken from the year 2022 to ensure that the study remains relevant to the latest findings regarding this topic. The various research reviewed in this paper are summarised in Table 3. Included are the input variable, the date the data was collected, and the country where the rainfall forecast model was executed. For rainfall prediction modelling, meteorological and hydrological variables were employed as inputs in the majority of studies. The input variables used in the rainfall prediction models reviewed here are discussed in subsequent sections.

In terms of study area, there are a total of 22 countries involved as case studies and, India has the highest number of articles that focus on rainfall forecasting followed by China, Indonesia, Australia, USA, Taiwan, Nigeria, Saudi Arabia, Pakistan, Ecuador, and Malaysia; while other countries highlighted in Fig. 2 have one relevant case study each. It is evident that countries facing climate crisis such as drought and floods take rainfall forecasting seriously to ensure the nations livelihood and resources are taken care of.

2.1. Classification of studies

The different kinds of input data used by the models to make predictions about rainfall, can be used to categorise the various kinds of rainfall forecasting studies. Many of the articles under consideration use either hydrological data or meteorological data as inputs. The data in all the articles was also structured in a way that makes it easy to compile and analyse. Input data used consideration are depicted in Fig. 3.

2.2. Meteorological inputs

Observational meteorological data pertain to atmospheric conditions, for instance temperature, dew point, wind direction, wind speed, cloud cover, cloud layer(s), ceiling height, visibility, current weather, and precipitation amount are all included in these data sets. Meteorological data are extensively utilised to forecast variations in precipitation. About 25 papers reviewed in this paper fully depend on meteorological data (Table 1). Papers from [13–15] commonly uses temperature and humidity as their input data. Besides the stated data, [16,17] uses radar echo and CHIRPS spatiotemporal data respectively as their meteorological independent variables.

2.3. Hydrological inputs

The collection, analysis, and use of hydrological data are necessary for getting good results in many forms of hydrological modelling. Consistently, hydrological indicators such as tide level and outflow have been used to anticipate precipitation. For this review paper, there are a

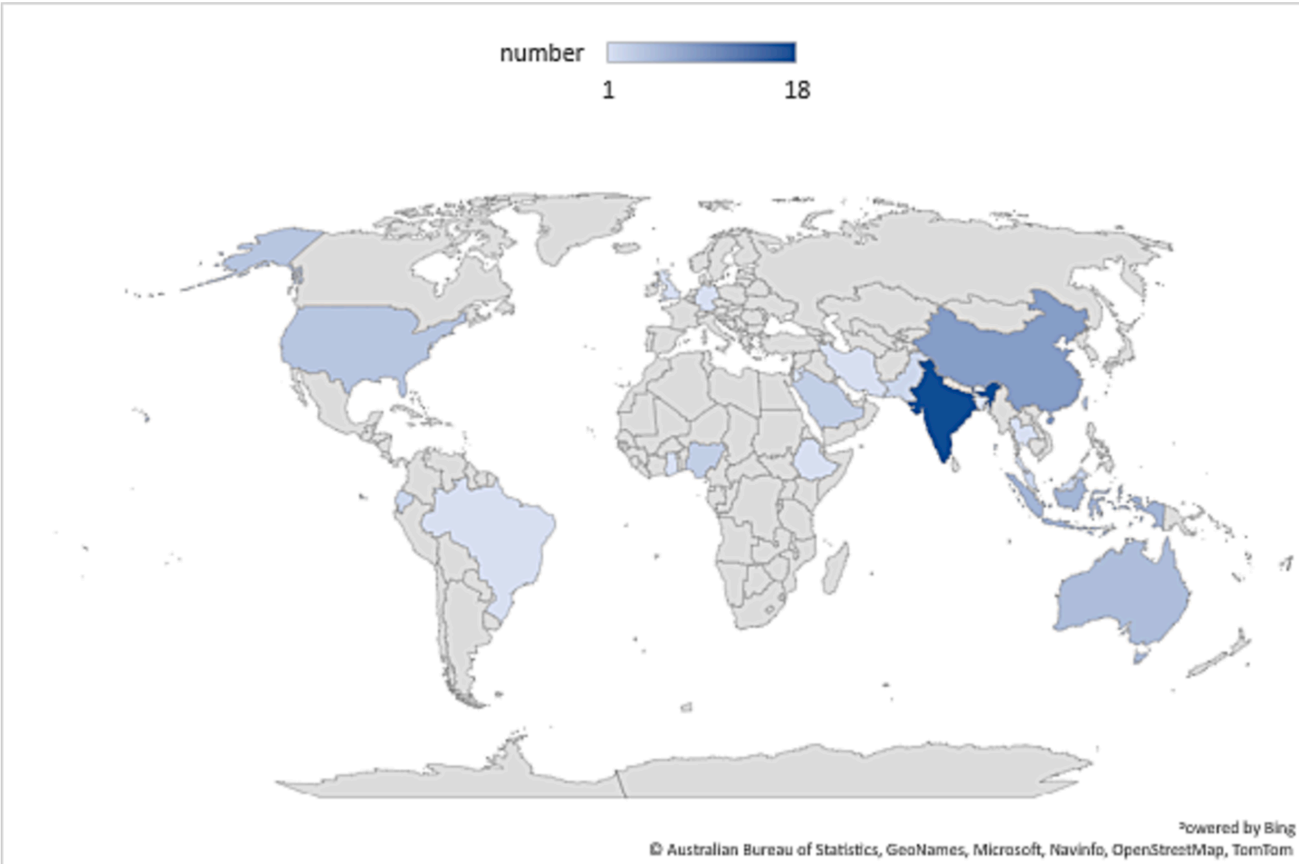

Fig. 2. Study areas according to number of articles.

total of 31 research papers that uses hydrological data inputs which is more than those that used meteorological inputs. The reason being is because most of these papers that falls under this category only uses rainfall as the input [18–22]. However, there are 14 other papers that require a combination of both meteorological and hydrological independent variables [2,9,15,23,24].

2.4. Rainfall predictive models

In order to predict the future rainfall efficiently, recent and previously recorded data is used to forecast rainfall. In this study, three primary types of predictive models were analysed and compared to determine the most accurate model to date. Machine learning, remote sensing and hybrid models were analysed provided that this review is addressing rainfall forecasting. The overall process flow is given in Fig. 4.

2.5. Machine learning

Machine learning is a subset of artificial intelligence that use algorithms and statistical models to enable an unprogrammed machine to automatically learn and improve based on data. On the other hand, deep learning is a type of machine learning that involves the use of neural networks to learn complex patterns and relationships in data. Both machine learning and deep learning have been applied to rainfall forecasting in a number of ways. For instance, machine learning algorithms have been used to find patterns and links in historical rainfall data that can be utilised to provide more precise forecasts. This entails training a model on big rainfall data sets and utilising it to predict future precipitation amounts. One of the primary benefits of utilising machine learning and deep learning for precipitation forecasting is their capacity to process vast amounts of data. This permits the integration of different data sources, like as satellite imaging, radar data, and ground-based observations, which can provide a fuller and more accurate picture of the status of the atmosphere and the likelihood of rainfall. Moreover, machine learning and deep learning algorithms can be trained to produce predictions at a very granular geographical and temporal scale. This enables the creation of more specific and localised forecasts, which can be valuable for a range of applications, including agriculture, water resource management, and disaster response.

In order to train and test the models, large quantities of high-quality data are required. This is one of the primary problems of employing machine learning and deep learning for rainfall forecasting. This can be difficult to obtain in some regions, particularly in developing countries where weather observation networks are often limited. Additionally, the performance of these algorithms can be affected by factors such as the quality of the data and the complexity of the underlying physical processes. Despite these challenges, machine learning and deep learning have demonstrated their potential to improve the accuracy and reliability of rainfall forecasting. For example, a study published in the journal Environmental Research Letters found that a machine learning algorithm outperformed traditional statistical techniques in predicting rainfall in the state of Texas. Another study published in the journal Advances in Atmospheric Sciences found that a deep learning algorithm was able to make more accurate short-term rainfall forecasts than traditional physical models.

Based on Table 2 there are a total of 56 papers that uses machine learning (ML) as their rainfall predictive model. This shows that this predictive measure has gained popularity these past years. To further elaborate, the linear regression is a simple statistical model that can be used to predict rainfall based on historical data, there are a number of other machine learning models that can be employed to make such

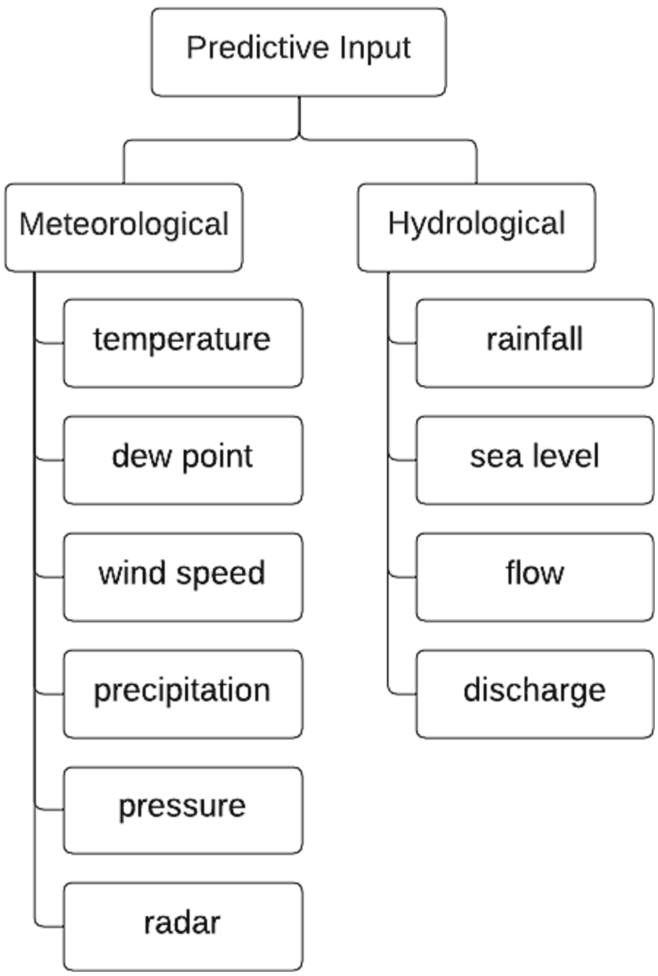

Fig. 3. Types of predictive parameters.

predictions. It assumes a linear correlation between predictor variables (such as climate and weather) and outcome variables (rainfall). Decision-tree-shaped algorithms can be utilised to make predictions based on previously established criteria. Using variables such as humidity, temperature, and wind speed, a decision tree could be constructed to forecast rainfall. Using a random forest ensemble model, which combines the outputs of multiple decision trees, is one way to improve the accuracy of predictions. The system generates a large number of decision trees and uses their average predictions to draw a conclusion. Support Vector Machine (SVM) techniques can be used to tackle both classification and regression problems. By identifying a hyperplane that splits the data into distinct classes or groups, they can be used to anticipate rainfall based on previous data. Recurrent Neural Networks (RNNs) are a sort of neural network that can be used to analyse time series data, as is frequently the case in the field of precipitation forecasting. RNNs excel at recognising patterns in sequential data and can be used to forecast future precipitation using historical weather data.

2.6. Remote sensing

Utilizing aircraft or satellites, remote sensing (RS) is the scientific practise of remotely gathering information about distant things or locations. Meteorology, hydrology, and agriculture can all benefit from the use of remote sensing in weather forecasting [71].

When a sensor is not physically in close proximity to an object, it is said to be remote sensing. Clouds, rainstorms, tropical cyclones, and cold and warm fronts are all examples of interesting meteorological systems, and the position and development of these systems is information of interest in the field of meteorology. The transmission of information from an object to a sensor through some intermediary medium calls for a material carrier. Remote sensing relies on electromagnetic radiation as its information carrier, and the result of such a system is often an image of the observed object. It is the object's electromagnetic radiation and its interaction with the medium between the object and the observer that determines the final appearance of the image. Remote sensing is used in a wide variety of disciplines. Cloud- and moisture-sensing meteorological satellites, as well as weather radars

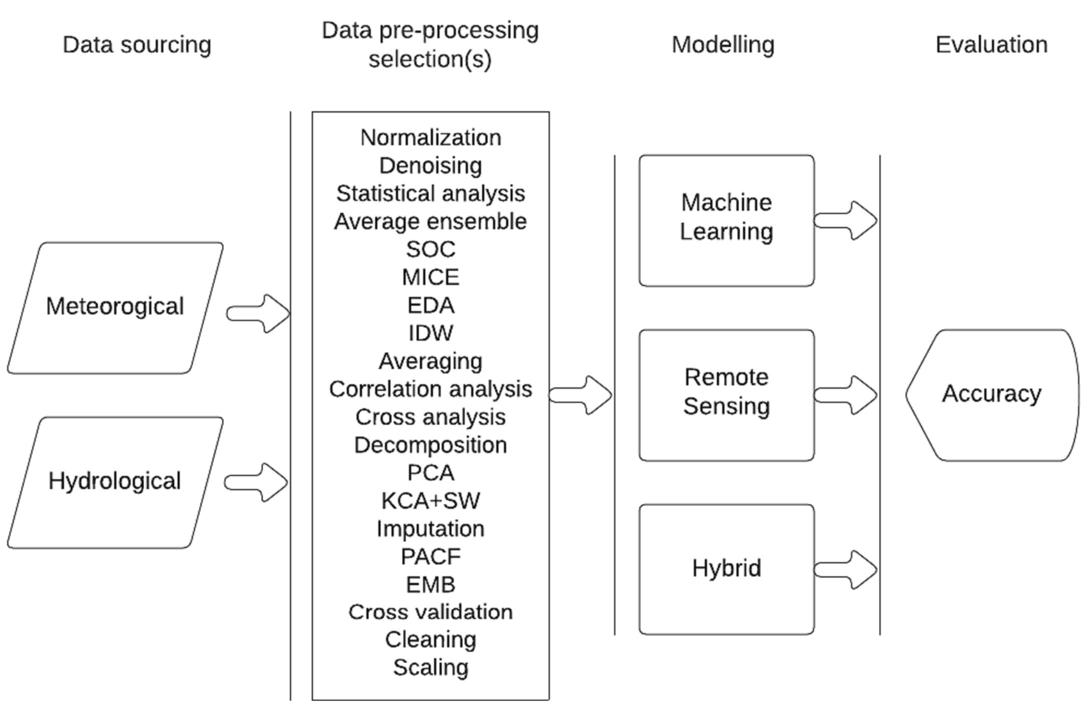

Fig. 4. Rainfall prediction process.

Table 2
Studies on machine learning models.

Research Article	Machine Learning
[13]	DCNN
[14]	NB, KNN, RF, LR, XG-Boost and CNN
[17]	RPM-DPS, RPM-KC, RPM-MM and RPM-DP
[18]	MLR, DTR, RFR, XGBoost and ANN
[19]	ANFIS
[20]	M5, RF, SVR-poly, SVR-RBF, MLP and LSTM
[21]	ANN and SARIMA
[22]	IDF
[23]	CNN and ARIMA
[24]	MLP, SVR, LGB, XGB and RDF
[28]	SVR and MLP
[29]	DT, RF, MLP, XGB and KNN
[30]	Conv1D-MLP, deep MLP and SVR
[31]	ANN
[32]	COMFO-DLRP, MLP, 1-DCNN, LSTM and DWRPM
[34]	MPR, ANN, ANFIS and SVM
[35]	LSTM, MC-LSTM, SAC-SMA and NVM-Rv2
[36]	M5 Pruned Model Tree and M5 Un-Pruned Model Tree
[1]	DT, NB, KNN, SVM and Proposed Fussed ML
[38]	GB, Pruned DT and Original DT
[39]	CEEMDAN-PSO-ELM, PSO-ELM, ELM and LSTM
[40]	KNN, DT, RF and NN
[41]	LSTM, MLP, KNN, SVM and DT
[42]	IFS, RR, DNN (MSE, MS-SSIM, WMSE-MS-SSIM)
[43]	(stacking) KNN, XGB, SVR and ANN
[44]	KNN, LR, SVM, RF, NB, NN and LSTM-PCA
[45]	ID3, SVM, NB, KNN, Fuzzy DT, DDT, C4.5, LMT, M5 Tree and GWLM-NARX
[46]	NMME
[47]	M5 Model
[48]	LSTM, BiLSTM, ZSG-based LSTM and ZSG-based BiLSTM
[49]	CSMO-OKRR, MSRF-DL (600,500,300,800) and CNN
[50]	SVM (EXP-G1D1 and EXP-G2D2)
[51]	LR, SVM, CNN
[53]	ELM, ARIMA, BPNN, WPD-ELM, WPD-ARIMA and WPD-BPNN
[54]	IFS, TRU-NET, HCGRU and U-NET
[56]	CSIRO-Mk3-6–0, Assembly, GISS-E2-R, IPSL-CM5A-MR, MIROC-ESM
[57]	ANN
[58]	FFNN, CFNN, PATTERNNET, ACO-FNN, ACO-CFNN and ACO-PATTERNNET
[60]	FFBNN
[61]	RF
[62]	NAR-ANN
[64]	ANFIS
[65]	LR, MLP, CNN, LSTM, GRU, BLSTM and BLSTM-GRU
[66]	BPNN and RBFNN
[67]	ELM, DLCMMELM, and PSO-DLCNNELM
[68]	LR, FC-LSTM, LSTM, ConvLSTM and Tiny-RainNet
[69]	GAMLSS
[70]	BPNN, MLP-FFN, HNN (Gradient Descent) and HNN (FPA)
[71]	CSA
[72]	Ensemble combinations of (SVM, C4.5, ANN, NB and RF)
[74]	RF, SVM and NARX
[76]	SVM, NB, KNN, DT and MLP
[77]	BPN, SVR
[78]	Holt-Winters, ARIMA, ELM, RNN with Relu, RNN with Silu, LSTM, Intensified LSTM
[79]	ANN (M1 and M2)

that scan for wet areas, fall under this category.

There are a number of benefits to utilising remote sensing for precipitation forecasting. For instance, remote sensing data can improve the accuracy of rainfall estimates when compared to conventional ground-based methods, which typically rely on a smaller number of rain gauges. Additionally, in regions where rain gauges are scarce, remote sensing can provide data from a larger area than conventional methods. Remote sensing's ability to offer real-time or near-real-time rainfall estimations enables early alerts and reactions to impending flooding and other weather-related risks. In addition, it can be less expensive than conventional methods because it can be performed remotely and does not require the maintenance of ground-based equipment. The collection of remote sensing data can reveal rainfall trends and patterns over time, which is useful for future planning and forecasting. Remote sensing can increase the precision, timeliness, and cost-effectiveness of rainfall forecasting, which are all essential for averting or decreasing the severity of weather-related calamities.

Table 3
Studies on remote sensing models.

Research Articles	Remote Sensing
[2]	GFS
[24]	FBP
[27]	MESONET, WSR-88D, CMORPH and 3B42
[30]	GCM
[33]	OBS and MMM
[37]	WRF-GSI, WRF-GSI_noDA, WRF_GSI_lidar and WRF-GSI_lidar_hzscl
[42]	TRMM and QM
[46]	CanCM3, CanCM4, CCSM3, CCSM4, CM2p1
[50]	CFSR
[52]	MJO
[77]	ESN, Deep ESN

In spite of remote sensing's usefulness in rain prediction, its limitations should not be ignored. Local variations in rainfall, such as those that occur in small catchments or urban areas, may not be captured by remote sensing data due to their coarse spatial and temporal resolution. Due to its reliance on clear atmospheric conditions, remote sensing can be negatively impacted by weather phenomena such as clouds, fog, and other atmospheric particles. It is challenging to get an accurate reading of rainfall using remote sensing data due to environmental factors like vegetation cover. To ensure accuracy, remote sensing data must be calibrated against ground-based measurements, which can be a time-consuming and laborious process. Although remote sensing can save money in some situations, it also requires specialised equipment and trained personnel, which can be prohibitive in others. Overall, remote sensing can be useful for rainfall forecasting, but it's important to keep these caveats in mind and use a combination of methods to get the most accurate and reliable results.

According to Table 3, rainfall can be predicted using a number of remote sensing models. Rainfall can be detected by passive microwave sensors by measuring the microwave radiation emitted by the atmosphere. These sensors can provide information regarding the intensity and distribution of rainfall over a vast area. Using radio waves, Doppler radar measures the velocity and intensity of raindrops in the atmosphere. By analysing the Doppler shift of the radar signal, the speed and direction of rain clouds, as well as the intensity and distribution of precipitation, may be determined. Using visible and infrared imaging sensors, one can detect cloud and raindrop reflection and emission of sunlight. By analysing brightness and temperature patterns, these sensors can provide information about the extent and intensity of rainfall. Using laser beams, Lidar measures the distance between raindrops and other atmospheric particles. By analysing the time required for the laser pulse to return to the sensor, it is possible to estimate the location, velocity, and size of raindrops, as well as the intensity and distribution of rainfall. Radiosondes are balloon-borne sensors that measure atmospheric variables like temperature, pressure, humidity, and wind speed. By tracking the movement of radiosondes in the atmosphere, it is possible to estimate the amount and distribution of rainfall over a large area. Satellites in geostationary orbit can continuously monitor the atmosphere over a vast region. These satellites can offer information on the intensity and spread of rainfall by detecting the temperature and moisture content of clouds. Distinctive remote sensing models have distinct advantages and disadvantages, and some may be better suited to specific applications or regions. Frequently, a combination of models is required to generate the most precise and trustworthy rainfall forecasts.

Table 4
Studies on hybrid models.

Research Articles	Hybrid
[14]	CNN-LSTM
[15]	ISA-PredRNN
[16]	Convolutional LSTM-AT with ArcGIS
[24]	CMIP5 with FBP
[9]	CGAN
[25]	GPS
[26]	(MLP, RF, C&RT, SVM and KNN) with radar and TB
[41]	NMSA
[55]	GRI_FCN, GRI-RRI_MCNN and RMMLP
[59]	Conv2D, Conv2D-GRU and Conv3D-GRU
[63]	PERSIANN-CDR and (NARX, SM2RAIN) with AMSR-E
[73]	MEMS (RF, SVM, BPNNs and LSTM)
[75]	Himawari-8 for Multivariate LSTM and RF, IMERG data for Multivariate LSTM and RF

2.7. Hybrid model

Combining the advantages of remote sensing and machine learning algorithms can result in a powerful hybrid model for rainfall prediction. A hybrid model will typically begin by gathering information on regional precipitation patterns from remote sensing instruments such as radar or satellites. Following that, the data would go through a pre-processing stage to remove any potential noise or interference. The pre-processed data would then be examined to determine which characteristics, such as rainfall intensity, cloud cover, and temperature, are most important for forecasting future rainfall. These characteristics would then be fed into a machine learning algorithm trained on a historical dataset of weather conditions and rainfall measurements. After the machine learning model has been trained, precipitation forecasts can be made using the input features gathered from remote sensing instruments. Finally, the model's predictions would be compared to actual rainfall measurements. A hybrid remote sensing and machine learning model is likely to provide more accurate and timely rainfall predictions, which can be critical in avoiding or mitigating the effects of weather-related disasters. It should be noted, however, that such models can be complex, necessitating knowledge of both remote sensing and machine learning, as well as careful calibration and validation.

There are advantages to using a model that combines machine learning and remote sensing to forecast rain, but there are some limitations. When using a hybrid of machine learning and remote sensing for rainfall prediction, it is critical to carefully consider limitations such as limited generalizability, limited interpretability, lack of transparency, and training data quality. To accomplish this goal, it may be necessary to invest time and money in gathering and training with high-quality data, verifying the accuracy of the model's predictions, and consulting with relevant stakeholders to ensure the model is appropriate for the intended application.

It can be observed that in Table 4 that the hybrid between machine learning and remote sensing commonly occurs when remote sensing is used as the input parameter to the machine learning predictive models [28,75].

3. Evaluation

Another useful category for rainfall forecasting is time horizons of estimated output. There are two primary time horizons to consider: the long and short term. The former horizon will be utilised more frequently in the future for urban and agricultural planning, where monthly and annual rainfall data is crucial. Understanding the final horizon involves familiarity of brief variations in rainfall and how they are affected by ongoing climate change. Since these prediction models produce a consistent output, the algorithms used in the papers under evaluation are regression algorithms. There are numerous metrics for evaluating

Table 5
Time Phases of Rainfall and Evaluation Procedures.

Research Article	Time Scales	Performance Indicators
[13]	monthly	Error rate and Accuracy
[14]	–	Accuracy, Precision, Recall and F1-Score
[15]	daily	POD, FAR, CSI, HSS and MSE
[16]	monthly	RMSE and MAE
[17]	daily	Accuracy, Precision, Recall, F-measure, Specificity and RMSE
[18]	monthly	MAE and R^2
[19]	monthly	RMSE, R and R^2
[20]	monthly	R, MAE, RMSE and OI
[21]	monthly	RMSE and MAE
[22]	annually	SME
[2]	daily	CC, RMSE, ME and BIAS
[23]	monthly	RMSE and MAE
[24]	monthly	PCC, ACC, IA and MAE
[9]	hourly	POD, FAR and CSI
[25]	minutes	FA and TD
[26]	minutes	MAE, MSE and SD
[27]	hourly	POD, FA, RMSE
[28]	annually	MSE, R and MAE
[29]	annually	accuracy, precision, recall and f-measure
[30]	daily	RMSE, R and NSE
[31]	monthly	MAE, RMSE, Max Rainfall, R, R^2
[32]	monthly	MSE and RMSE
[33]	seasonal	Predicted vs Actual
[34]	monthly & annually	R^2, RMSE, AIC and C
[35]	daily	NSE, KGE, Pearson-r, Alpha-NSE, Beta-NSE, FHV, FLV, FMS and Peak-Timing
[36]	–	RMSE, MAE and R^2
[37]	hourly	improvement %
[1]	–	Miss Rate, Accuracy, Negative Prediction Value Positive Prediction Value, Likelihood Ratio Negative, Likelihood Ratio Positive, False Negative Value, False Positive Value, Sensitivity and Specificity
[38]	–	Accuracy, Error, Recall (Rainfall), Recall (No Rainfall), Precision (Rainfall), Precision (Rainfall) and Cohen Kappa
[39]	monthly	MAE, RPE, RMSE and NSE
[40]	monthly	Misclassification Rate, MSE and AUC
[41]	daily	RMSE, NRMSE, MAPE, NSE and R^2
[42]	hourly	HSS, F1, CSI, POD and FAR
[43]	monthly	R^2, RMSE and MAE
[44]	daily	Accuracy
[45]	–	MSE and R
[46]	monthly	RMSE, MAE and R^2
[47]	–	RMSE, MAE and R^2
[48]	daily	MSE, NSE and MAE
[49]	daily	MSE and RMSE
[50]	daily	ACC, PPV, POD and F1-score
[51]	monthly	MAE
[52]	weekly	COR and RMSE
[53]	annually	RMSE, MAE, R and NSEC
[54]	daily	RMSE, R10 RMSE and MAE
[55]	hourly	MAE, RMSE and CE
[56]	daily	NSE, KGE, PBIAS, MARE, RMSE, MAE and MCM
[57]	annually	AAE, MAE, RMSE, MASE and PP
[58]	monthly	Precision, Sensitivity, Specificity, Accuracy and Time
[59]	–	CSI, HSS, MSE, MAE, B-MSE, B-MAE
[60]	monthly	MSE and R
[61]	monthly	R^2
[62]	annually	MSE and R
[63]	daily	R^2, RMSE and NSE
[64]	daily	RMSE, MSE, R and MAPE
[65]	daily	MSE, RMSE, R^2 and Correlation
[66]	monthly	R, MSE, MBE, and MAE
[67]	–	MAD
[68]	hourly	RMSE, CC, MB and MAE
[69]	annually	MAE, PBIAS, RMSE and R^2
[70]	–	accuracy, precision, recall and f-measure
[71]	monthly	accuracy

(continued on next page)

Table 5 (*continued*)

Research Article	Time Scales	Performance Indicators
[72]	daily & monthly	Precision, Recall and F-Measure
[73]	minutes	MAE and RMSE
[74]	monthly	NSE, KGE, PBIAS and RMSE
[75]	daily	R, RMSE and NSE
[76]	–	Precision, Recall and F-Measure
[77]	hourly	RMSE, POD, FAR, TS
[78]	daily	Accuracy, RMSE, Losses and Learning Rate
[79]	monthly	Regression Value and MSE

the efficacy of machine learning regression methods, but they all boil down to one: the degree of correspondence between the predicted and observed values. Indeed, performance metrics are essential for determining how closely the proposed model matches the actual values of its output variables to the desired values. Selecting the appropriate metrics to evaluate the model's effectiveness is crucial in this situation. Statistical measures like the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Coefficient of Determination (R^2) are often employed as performance metrics for assessing the accuracy of a prediction or forecasting model [80–84]. In Table 5, provides an overview of the various time steps and assessment metrics used to test the model's predictions.

4. Conclusions and recommendations

Due to the vast and complexity of some studies review in this paper, there are indeed several limitations and recommendations that were highlighted earlier. To start off with limitations, some papers have limited performance indicators which do not fully validate the accuracy of the tested predictive models [18]. To add, is often seen that some predictive models were not being compared with other existing predictive models, and very commonly this occurs because the authors' main objective is to testify the relevance of a newly developed model and to only offer it as an alternative technique to specific time scales or regions [22,23,25,27]. In a few cases, the models would only take into consideration of the general input parameters in determining rainfall predictions without acknowledging external factors such as wind and geopotential height [24].

In terms of recommendations, many authors suggested multiple ways on how the newly developed model does can be improved. For instance, [17] recommended the incorporation of augmented flood data and physical model interpretation in order to make more accurate predictions. On the other hand, [54] suggested to combine Extreme Value Theory and ML to improve current TRU-NET.CC model.

When it comes to the best predictive model for rainfall prediction, it is almost impossible to conclude as specific models are catered to fit specific time scale, climate, region and seasons. However, if all of these papers are compared in terms of the extent of performance indicators used along with its greatest accuracy, it would have to be LSTM by [9] with detailed results of NSE = 0.81, KGE = 0.77, Pearson-r = 0.91, Alpha-NSE = 0.82, Beta-NSE = -0.03, FHV = -17.37, FLV = -2.49, FMS = -6.37 and Peak-Timing = 0.36 for their daily rainfall predictions. This proves the superiority of ML models specifically; the LSTM models are one of the commonly used models in rainfall prediction. [30] also suggested on experimenting with LSTM, this despite having achieved high accuracy for their SVR model (R = 0.9989, MAE = 0.085, and RMSE = 0.1024). To conclude, this machine learning has been proven to excel in rainfall predictions regardless of climate and time scale. However, looking at the lack of remote sensing and hybrid models, it is recommended that these two types of predictive models to be explored deeper to unlock better and more important findings for sake of a well-nourished and protected society, and also to use good fine technology for solving problems. It is the ardent hope of the authors that the findings in this review analysis can influence future research and improve the accuracy of rainfall forecast algorithms.

Ethics approval: Not applicable.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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