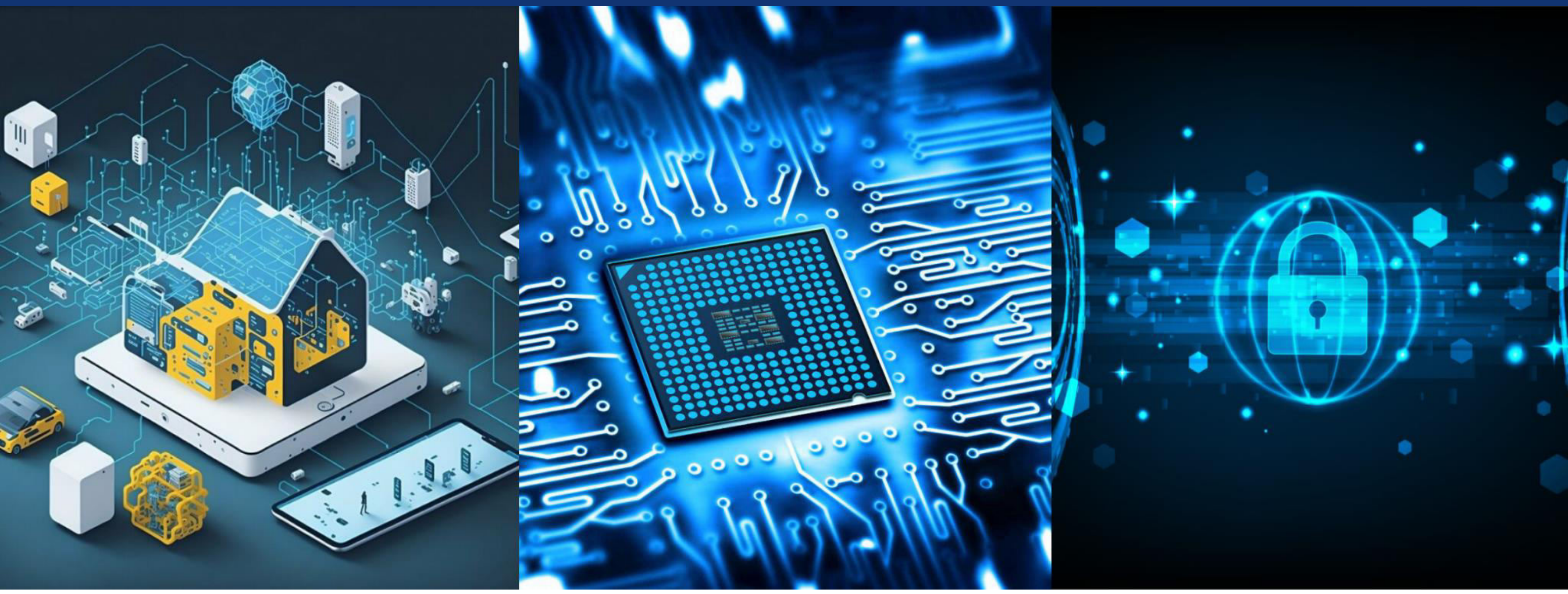
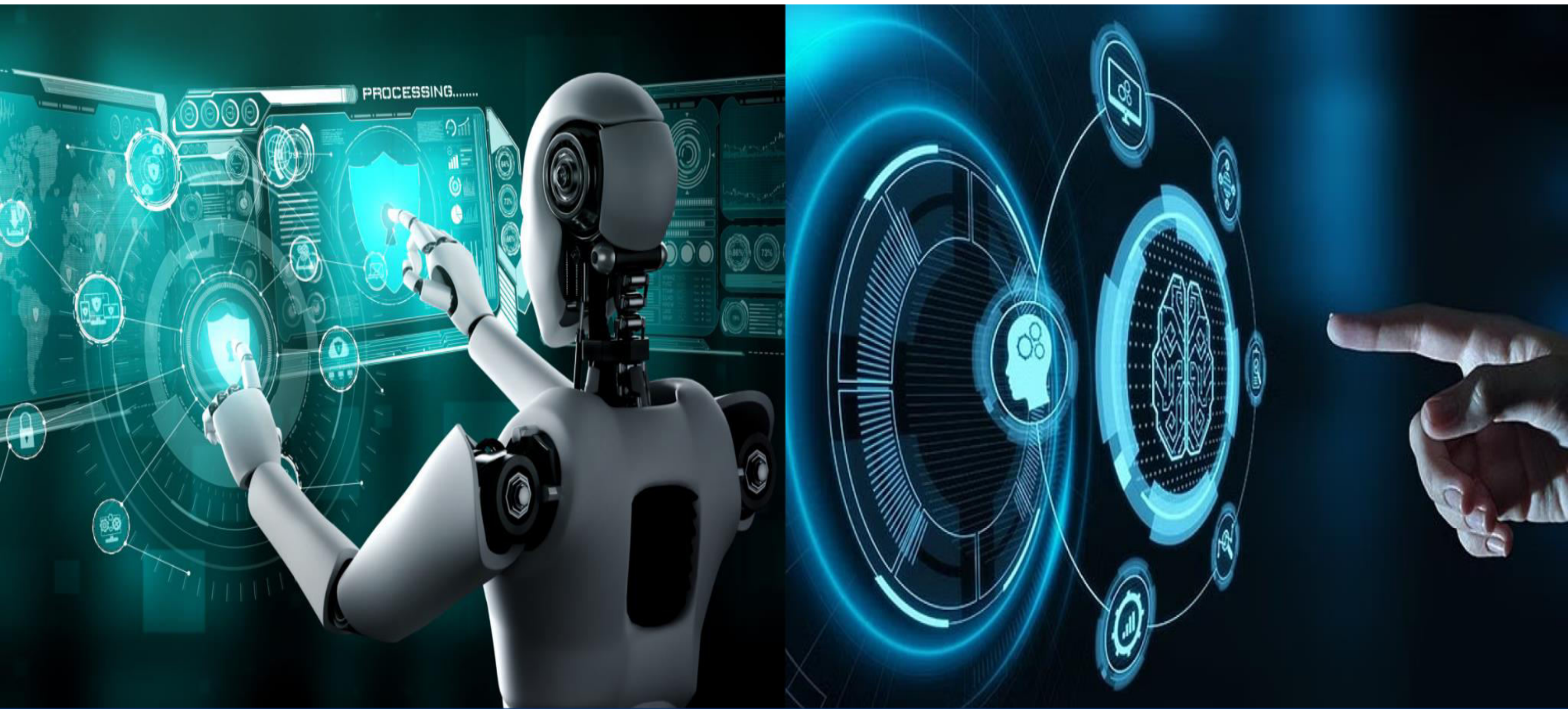
ISSN(O): 2320-9801

ISSN(P): 2320-9798



# International Journal of Innovative Research in Computer and Communication Engineering

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)




**Impact Factor: 9.927**

**Volume 14, Issue 7, July 2026**

www.ijircce.com   ijircce@gmail.com   +91-9940572462   +91 63819 07438

© 2026 IJIRCCE | Volume 14, Issue 7, July 2026 DOI: 10.15680/IJIRCCE.2026.1407070

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 9.927| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

# A Review on Deep Learning Based Flood and Drought Prediction System

**Aditya Nagpurkar[1], Krutika Thakur[2], Aarushi Ghadge[3], Yash Mulankar[4]**

B. Tech Scholar, Department of Computer Engineering, St. Vincent Pallotti College of Engineering & Technology, Nagpur, Maharashtra, India[1]

B. Tech Scholar, Department of Computer Engineering, St. Vincent Pallotti College of Engineering & Technology, Nagpur, Maharashtra, India[2]

B. Tech Scholar, Department of Computer Engineering, St. Vincent Pallotti College of Engineering & Technology, Nagpur, Maharashtra, India[3]

B. Tech Scholar, Department of Computer Engineering, St. Vincent Pallotti College of Engineering & Technology, Nagpur, Maharashtra, India[4]

**ABSTRACT:** Floods and droughts are among the most severe natural disasters, significantly affecting the human life, agriculture, water resources, and economic development. With climate change the occurrence of such events has become more frequent and intense, making predictions with the traditional statistical and hydrological models more difficult. With the recent developments of Deep Learning (DL) technologies that offer powerful solutions for producing validated answers related to complex spatial and temporal data in the environment. This review provides an overview on deep learning (DL) technique including the convolutional neural network (CNN), the long short-term memory (LSTM), convLSTM, and the hybrid models for flood and drought forecast. It highlights the application of remote sensing, satellite information and climate data in enhancing the achievement of forecasting and the performance of forecasting. It covers the application of remote sensing, satellite data and climate data to enhance forecast skill. Some key research gaps were also identified, such as the lack of integration between flood and drought prediction, the lack of interpretability of models and the lack of real-time forecasting. The developed observations led to the formulation of hybrid CNN-LSTM network integrated into Explainable Artificial Intelligence (XAI) as potential frameworks for developing accurate, trustworthy, and understandable early warning systems for disaster management and climate adaptation.

**KEYWORDS:** Deep Learning, Flood Prediction, Drought Prediction, CNN, LSTM, Explainable Artificial Intelligence (XAI), Remote Sensing, Climate Change, Disaster Management.

## I. INTRODUCTION

One of the most serious environmental problems in the world today has been the extreme hydrological events like floods and droughts. These catastrophic events have a tremendous impact upon human life, agriculture, infrastructure, environment, and the economy. Such events have become much more common and severe over the last few decades due to rapid urbanisation, changing land use and global climate change. Therefore, it is important for governments and disaster management agencies to have reliable systems for prediction, early warning warnings and helping to reduce the loss of life and property caused by the disaster. The traditional flood and drought prediction methods include mainly statistical analysis, physical hydrological models and numerical weather prediction methods. These methods are currently popular and have been in standard application for a long period of time, but they rely on manually formulated equations and assumptions that do not reflect the highly nonlinear connections between climatic, hydrologic, and environmental parameters. Additionally, such models often demand a deep understanding of the domain and tend to lose prediction accuracy in facing unpredictable climate shifts or areas where there is only limited past data. Artificial Intelligence (AI) and Deep Learning (DL) have brought about novel solutions for environmental monitoring and disaster prediction in recent years. The deep learning models can automatically derive meaningful representations from large and complex data sets without feature engineering. Rapid advancements in high-resolution satellite imagery,

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 9.927| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

remote sensing products, climate data, and cloud-based geographic information platforms have fueled the growth of the application of AI techniques to hydrological forecasting. In particular, Convolutional Neural Networks (CNNs) have shown to be highly capable of extracting spatial information from satellite images with many relevant applications, such as flood detection and inundation mapping. As such, Long Short-Term Memory (LSTM) networks are able to learn the long time-series relations from the sequential climate data, which allows the precise forecast of droughts from climate parameters including rainfall, temperature, humidity, soil moisture and vegetation index. However, these models have shown marked advantages over traditional machine learning and statistical approaches in recent investigations for their capacity to model nonlinear, complex relationships among vast amounts of environmental data. Meanwhile, multiple researchers put forward hybrid DNN architectures with the capacity to merge the spatial and temporal information in both the CNN and LSTM networks. Recent advanced methods such as.ConvLSTM, Attention Mechanisms, Wavelet Transform, Graph Neural Networks, and Transformer-based architectures are also studied to enhance the forecasting capability. Also, the processing of big satellite datasets, like in the case of Google Earth Engine (GEE), has become much easier, allowing environmental monitoring in near real-time across vast geographical areas. Although these advances have been made, numerous current systems lack the ability to be interpreted readily, be computationally cheap, and to make predictions for both flood and drought, instead being either flood or drought prediction systems. Naturally, an important challenge in the ongoing research is the "black-box" of the deep learning models. In general, these models can be good at predicting, but they offer little insight in what is driving their predictions. Such unexplainable actions undermine user trust and limit the use of AI-driven solutions in real-world applications by disaster management organizations and policy makers. Furthermore, most of the present models only use one of the two pieces of information: either spatial and from satellite data or temporal and from meteorological observations, which leads to incomplete understanding of complex hydrological processes. Overcoming these restrictions, it has become necessary to develop an environment-integrated prediction framework that can combine diverse environmental datasets, and at the same time learn spatial and temporal environmental patterns in flood and drought events. Any system developed should be more accurate at making predictions and should offer voters through its results a clear and understandable option for decision making. Seamless integration of XAI with hybrid deep learning systems has the potential to provide users with insights into how the model arrived at its predictions, while also maintaining high forecasting accuracy. The review paper gives a thorough analysis of recent deep learning techniques involved in flood and drought prediction (CNN, LSTM, ConvLSTM, hybrid architectures and explainable AI approaches). The comprehensive assessment of the existing methodologies, highlighting the research gaps in the field and the necessity for a consolidated Deep Learning based framework that addresses different remote sensing-based data to predict disasters accurately and reliably with the support of satellite images, climate time-series information and remote sensing data. Such an integrated approach can contribute to enhance early warning, build disaster preparedness and sustainable environmental management in the context of changing climate.

## II. LITERATURE REVIEW

Deep learning methods have recently emerged and received much attention to model non-linear, complex relationships in climate and water domain data, and consequently have been introduced to the field of hydrological prediction. Different types of architecture are investigated to enhance the accuracy of the prediction system of flood and drought, including Convolutional Neural Networks (CNN), Long Short-term Memory (LSTM), and hybrid models.

In this paper [1] the performance of three artificial intelligence models Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM) and Wavelet Adaptive Neuro-Fuzzy Inference System (WANFIS) was tested for flood and drought forecasting in arid and tropical climatic regions. River runoff data were used for flood forecasting and the Standardized Precipitation Index (SPI) was used for meteorological drought prediction. The comparative analysis showed that in terms of accuracy, CNN had the best performance in the task of flood prediction, while WANFIS had the best performance in the tasks of drought forecasting for various climatic conditions. The researchers found that using AI models is much more effective at capturing complex hydrological patterns, particularly those that are nonlinear, and that it provides more accurate predictions than traditional forecasting techniques.

This paper [2] presented an extensive survey of the deep learning models used for drought prediction problems such as Deep Neural Network (DNN), CNN, Multi-Layer Perceptron (MLP), Long Short Term Memory (LSTM) and hybrid deep learning models. The review noted that deep learning methods are now proving of great use in uncovering complex non-linear relationships in meteorological and environmental data sets and hence better forecasting droughts than the traditional machine learning models. The authors also discussed commonly used drought indices, some of the larger issues like data quality and model generalization, and the need for hybrid models and high quality datasets for the study of droughts in order to develop optimal future drought prediction systems.

In the paper [3] flash droughts have been reviewed and the use of Machine Learning (ML) and Deep Learning (DL) techniques in enhancing flash droughts have been explored. Nonlinear interaction among climatic variables caused flash droughts to develop quickly and in complex ways, which limits the ability of traditional drought indices and physical models to represent them. The authors have found that multi source environmental data coupled with ML and DL can drastically improve uncertainty in prediction, advance understanding on drought evolution, and boost the quality of early warning for drought management practices.

This paper [5] suggested a hybrid model of Bidirectional-LSTM deep learning model for precipitation forecasting to enable accurate drought forecasting. The proposed architecture takes advantage of the temporal relationships using Bidirectional LSTM layers from multi-variate meteorological time-series data followed by LSTM layers for final prediction. For prediction, the model showed a greater correct prediction ability and successfully learned the context information while minimizing over-fitting via dropout regularization. It is concluded that precise rainfall forecasting can help a lot in drought management and optimal drought resource planning; the proposed model only involves rainfall-based drought forecasting and does not involve multi-source satellite-based rainfall forecasting and flood forecasting.

In this paper [6] the drought prediction was evaluated through the use of Classification and Regression Trees (CART) and Random Forest algorithm to satellite-based TRMM and MERRA-2 datasets in Indonesia. The three-month SPI was used to classify the drought and the Random Forest model had been better than CART in prediction accuracy and Area Under the Curve (AUC) using the MERRA-2 data. Based on results of the study, soil surface temperature, NDVI, Multivariate ENSO Index (MEI) and Arctic Oscillation Index (AOI) were identified as important drought indicators and showcased the better performance of machine learning based on remote sensing materials in drought monitoring.

This paper [7] presented the Hydro-Informer, a Hybrid Deep Learning framework which combines CNN, Recurrent Neural Networks (RNN), LSTM and Multi-Head Attention models to achieve good water level and flood forecasting accuracy. The model was applied to groundwater data from Slovakia; it had an $R^2$ of 0.88 and proved to be successful in forecasting extreme flood events up to 12 hours ahead. The results showed that the proposed model with spatial feature extraction, temporal sequence learning, and attention mechanisms can enhance the forecasting accuracy, which helps effectively manage the flood and prepared for the disaster, particularly in the areas lacking the water management infrastructure.

This work [8] suggested a fast urban flood forecasting model under the condition of dynamic rainfall, which is the convolutional LSTM model. The model can effectively integrate temporal memory with convolutional operation to capture spatial and temporal properties of inundation and rainfall. They performed well, obtaining an average $R^2$ value of 0.964, which was higher than any other model models, CNN and CNN-LSTM, with a computation time that was much lower than any other physics based hydrological model. The study addressed urban floods, however, drought prediction was secondary in this study context.

This paper [9] has presented a detailed review of the various approaches used to predict droughts including statistical models, machine learning, deep learning, remote sensing technologies, meteorological observations and climate indices. The research also highlighted the strengths of the emerging artificial intelligence and deep learning techniques, which consistently outperform traditional statistics when using big data of spatial and temporal information. The authors emphasized the need to incorporate the remote sensing data, hydrologic and climatic records for more precise drought prediction and revealed challenges such as data availability and computational needs for future studies. research.

## III. PROBLEM STATEMENT

Climate change is increasingly making floods and droughts more common and intense thus posing a considerable threat to human life, agriculture, water resources and the economy. Some of the traditional statistical and hydrological models lack the ability to simulate the intricate nonlinear interaction between environmental variables, which may limit the prediction accuracy and late response in an early-warning system. While deep learning techniques have been shown to be valuable in forecasting the ability of either flooding or drought, however, previous studies have been targeted to a

© 2026 IJIRCCE | Volume 14, Issue 7, July 2026 DOI: 10.15680/IJIRCCE.2026.1407070

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 9.927| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

single forecasting problem, either floods or droughts. Additionally, existing models are mostly data-poor, and poorly able to adequately combine satellite-based spatial information and climate observations from the past. Many deep learning models are also poorly interpretable; that is, they are unclear as to why they make the prediction that they do. This means that there is the need for an integrated, accurate and comprehensible prediction system which could predict both flood and drought events from different environmental datasets.

## IV. PROPOSED WORK

This review suggests a deep learning framework to integrate Convolutional Neural Network (CNN) and a Long Short-Term Memory (LSTM) network for flood and drought prediction. CNN is used in the satellite image analysis from space to obtain their spatial features for flooding detection, and LSTM models the features over climate time-series data including rainfall, temperature, humidity, soil moisture, etc., to forecast drought. To enhance data quality and model performance, data pre-processing methods such as normalization and Wavelet Transform are used. Prediction results of both models are combined by a decision level fusion strategy to produce overall environmental risk forecast. In addition, Explainable Artificial Intelligence (XAI) is included to enhance the transparency of the models by offering explanations for the forecast. The plan proposed above seeks to improve the accuracy of predictions, provide early warning systems and help disaster management authorities to make informed decisions.

## V. CONCLUSION

This is a review paper in which a detailed survey of deep learning approaches to predicting floods and droughts is discussed. Different CNN-based, LSTM-based, hybrid neural network-based and XAI models have been investigated and analyzed with respect to the enhancements it brings in hydrological disaster forecasting. Current methods provide satisfactory prediction performance, but also have some drawbacks in terms of predicted disaster and the integration of multiple sources.Despite the satisfactory prediction performance of the existing methods, there are also some limitations such as the prediction of disaster in isolation, limited integration of multi-source data and the lack of model interpretability. Considering the research gaps identified, a CNN-LSTM-based XAI framework was proposed for accurate and reliable prediction of flood and drought events while achieving Grand Transparency. This is foreseen to improve the early warning system and help in effective decisions-making to disaster management authorities while also making a contribution for sustainable environmental monitoring and climate resilience.

## REFERENCES

[1] K. E. Adikari, S. Shrestha, D. T. Ratnayake, A. Budhathoki, M. S. Shanmugam, and M. N. Dailey, "Evaluation of Artificial Intelligence Models for Flood and Drought Forecasting in Arid and Tropical Regions," Environmental Modelling & Software, vol. 144, Art. no. 105153, 2021.

[2] W. Almikaeel, A. Šoltész, L. Čubanová, and D. Baroková, "Hydro-Informer: A Deep Learning Model for Accurate Water Level and Flood Predictions," Natural Hazards, vol. 121, no. 11, pp. 3959-3979, 2025.

[3] A. Morshed-Bozorgdel, M. V. Anaraki, S. Farzin, and M. Kadkhodazadeh, "Integrating Deep Learning and Copula Models for Flood-Drought Compound Analysis in Iran," Water, vol. 17, no. 24, Art. no. 3479, 2025.

[4] A. Gyaneshwar, A. Mishra, U. Chadha, P. M. D. Raj Vincent, V. Rajinikanth, G. Pattukandan Ganapathy, and K. Srinivasan, A. (2023), A Contemporary Review on Deep Learning Models for Drought Prediction, Sustainability, 15(7), Art. no. 6160.

[5] B. B. Gupta, A. Gaurav, R. W. Attar, V. Arya, S. Bansal, A. Alhomoud, K. T. Chui, "Advance Drought Prediction Through Rainfall Forecasting with Hybrid Deep Learning Model," Scientific Reports, vol. 14, Art. no. 30459, 2024.

[6] U. W. Humphries, M. Waqas, P. T. Hliang, P. Dechpichai, and A. Wangwongchai, "A Deep Learning Perspective on Meteorological Drought Prediction in the Mun River Basin, Thailand," AIP Advances, vol. 14, no. 8, Art. no. 085026, 2024.

[7] uswanto, A. Naufal, Evaluation of Performance of Drought Prediction in Indonesia Based on TRMM and MERRA-2 using Machine Learning Methods, MethodsX, vol. 6, 2019. 1238-1251, 2019.

[8] A. Márquez-Grajales, R. Villegas-Vega, F. Salas-Martínez, H. G. Acosta-Mesa, and E. Mezura-Montes, "Characterizing Drought Prediction with Deep Learning: A Literature Review," MethodsX, vol. 13, Art. no. 102800, 2024.

[9] N. Nandgude, T. P. Singh, S. Nandgude, and M. Tiwari, "Drought Prediction: A Comprehensive Review of Different Drought Prediction Models and Adopted Technologies," Sustainability, vol. 15, no. 15, Art. no. 11684, 2023.
[10] F. A. Prodhan, J. Zhang, F. Yao, L. Shi, T. P. P. Sharma, D. Zhang, D. Cao, M. Zheng, N. Ahmed, and H. P. Mohana, "Deep Learning for Monitoring Agricultural Drought in South Asia Using Remote Sensing Data," Remote Sensing, vol. 13, no. 9, Art. no. 1715, 2021.
[11] K. Sundararajan, L. Garg, K. Srinivasan, A. K. Bashir, J. Kaliappan, G. Pattukandan Ganapathy, S. K. Selvaraj, and T. Meena, "A Contemporary Review on Drought Modeling Using Machine Learning Approaches," Computer Modeling in Engineering & Sciences, vol. 128, no. 2, pp. 447-490, 2021.
[12] S. Tyagi, X. Zhang, D. Saraswat, S. Sahany, S. K. Mishra, and D. Niyogi, "Flash Drought: Review of Concept, Prediction and the Potential for Machine Learning and Deep Learning Methods," Earth's Future, vol. 10, no. 10, Art. no. e2022EF002723, 2022.
[13] J. Xiao, Z. Wang, Y. Liao, Y. Yi, L. Zheng, B. Yang, H. Yu, X. Li, N. Hu, and C. Lai, "A ConvLSTM-Based Model for Urban Flood Prediction Under Dynamic Rainfall Patterns and Exploration on Its Extrapolation Capability," International Journal of Disaster Risk Science, vol. 16, pp. 1057-1073, 2025.
[14] J. Yu, T. Ma, L. Jia, H. Rong, Y. Su, and M. M. Abdel Wahab, "Multivariate Spatio-Temporal Modeling of Drought Prediction Using Graph Neural Network," Journal of Hydroinformatics, vol. 26, no. 1, pp. 107-124, 2024.
[15] Z. Zhang, D. Wang, Y. Mei, J. Zhu, and X. Xiao, "Developing an Explainable Deep Learning Module Based on the LSTM Framework for Flood Prediction," Frontiers in Water, vol. 7, Art. no. 1562842, 2025.
[16] M. M. Hamed, M. S. Nashwan, and S. Shahid, "Transformer-Based Network for Hourly and Multi-Step Ahead Streamflow Forecasting," Hydrological Sciences Journal, vol. 68, no. 11, pp. 1545-1562, 2023.
[17] S. I. Abba, Q. B. Pham, A. G. Usman, N. T. T. Linh, N. Al-Ansari, and X. C. Nguyen, "Emerging Evolutionary-Optimized Multi-Layered Ensemble Learning for Drought Index Prediction," Scientific Reports, vol. 12, Art. no. 14925, 2022.
[18] D. Li, X. Zheng, and S. Liu, "Cross-Regional Transfer Learning for Hydrological Forecasting in Ungauged Basins," Water Resources Research, vol. 59, no. 4, Art. no. e2022WR033100, 2023.
[19] V. A. Bento, C. M. Gouveia, C. C. DaCamara, and I. F. Trigo, "The 2017 Droughts in the Iberian Peninsula: An Explainable AI Approach to Vegetation Browning," Agricultural and Forest Meteorology, vol. 308, Art. no. 108560, 2021.
[20] O. Rahmati, H. Darabi, M. Panahi, Z. Kalantari and A. T. Haghighi, "Development of Novel Deep Learning Based Flood Susceptibility Mapping; A Case Study of Gorganrood Basin, Iran," Science of the Total Environment, 2020, vol. 742, Art. number 140557, 2020.

| Sr. no. | Author(s) & Year | Concept Used | Performance Evaluation Parameter | Claims by Concerned Authors | Our Findings |
|---|---|---|---|---|---|
| 1. | Adikari et al. (2021) | CNN, LSTM, WANFIS for flood and drought forecasting | RMSE, MAE, $R^2$, NSE, Correlation Coefficient | CNN achieved the best performance for flood prediction, while WANFIS performed best for drought prediction in different climatic regions. | CNN successfully captures spatial features for flood prediction but there remains a need for a single model that would be capable of predicting flood and drought simultaneously. |
| 2. | Gyaneshwar et al. (2023) | Review of DNN, CNN, LSTM, MLP and Hybrid Deep Learning Models | Accuracy, Precision, Recall, F1-Score (review comparison) | When sufficient data are available, deep learning models work better than traditional machine learning models for predicting drought. | The accuracy and robustness of prediction can be further improved by introducing more datasets and hybrid CNN-LSTM models. |
| 3. | Tyagi et al. (2022) | Machine Learning and Deep Learning | Prediction Accuracy, Drought Indices (SPI, | ML and DL integrated with multisource data | The satellite imagery and climate variables |

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 9.927| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

| | | | | | |
|---|---|---|---|---|---|
| | | for Flash Drought Prediction | SPEI, NDVI, ESI) | reduce uncertainty and improve flash drought prediction. | in conjunction with deep learning information can be used to aid in early drought detection. |
| 4. | Kuswanto & Naufal (2019) | Random Forest and CART using TRMM and MERRA-2 datasets | Accuracy, AUC, Classification Performance | Random Forest with MERRA-2 data provided higher drought prediction accuracy than CART. | The satellite imagery and climate variables in conjunction with deep learning information can be used to aid in early drought detection. |
| 5. | Almikaeel et al. (2025) | Hydro-Informer (CNN + RNN + LSTM + Multi-Head Attention) | $R^2$, MAE, RMSE | Proposed model achieved **$R^2$ = 0.88** and accurately predicted extreme flood events up to 12 hours in advance. | For improving the accuracy of flood forecasting and early warning-ability: Implementation of hybrid deep learning with attention mechanisms are highly effective. |
| 6. | Nandgude et al. (2023) | Review of Statistical, Machine Learning and Deep Learning Drought Prediction Models | Accuracy, Prediction Efficiency, Comparative Analysis | Deep learning methods provide better prediction accuracy than conventional statistical approaches. | Combining remote sensing data and deep learning models improve drought prediction. |
| 7. | Gupta et al. (2024) | Hybrid Bidirectional LSTM-LSTM for Rainfall Forecasting | Verify goodness of fit using MSE, Prediction_Accuracy, RMSE and MAE. | The Hybrid BiLSTM-LSTM outperform other methods for rainfall prediction while can also help in more precise drought prediction. | Temporal sequence learning with BiLSTM performes well, and it can be enhanced by integrating with CNN to enhance the forecasting of flood and drought in temporal sequence. |
| 8. | Márquez-Grajales et al. (2024) | Systematic Review of Deep Learning for Drought Prediction | Comparative Analysis of DL Models | LSTM is the most widely-used deep learning model, and SPI and SPEI are the most commonly used drought indices. | Diverse and location-specific hybrid deep learning systems based on multiple environmental data sources are needed. |

**Table 1:** Survey Table