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EMPIRICAL, CONVENTIONAL TO NEURAL NETWORKS TO ARTIFICIAL INTELLIGENCE: EVOLUTION OF WATER RESOURCES MODELLING IN RAJASTHAN, INDIA

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ABSTRACT

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Water resources management in Rajasthan faces growing demands because of the unpredictable rainfall patterns, semi-arid weather conditions and the growing demand of water in the context of population growth and agricultural expansion. Therefore, proper evaluation of hydrological processes is important in watershed management and sustainable water planning in the area. Traditional hydrological modelling procedures have been used and applied extensively over the years to formulate prediction of rainfall runoff relationship, elements of water balance and rainfall runoff dynamics within the catchments of Rajasthan-the river basins. These techniques can be useful in studying the productivity of surface runoff, evapotranspiration losses and ground water recharge. But there are often complex and non-linear interactive processes between climatic variation, change in land use and basin characteristics, and there is often low predictive power in semi-arid that is found by simple techniques of modelling. Mathematical simulation with rainfall and runoff artificial neural networks under MATLAB showed a high predictive potential to semi arid catchment systems with rainfall that is not exceeding 0-180 mm/day, whereas runoff was reached to up to 95 m³/s during turbulent seasons. The indices of the model showed that the performance of this model was consistent in the aspect of simulation accuracy in R²(0.72-90), radiation Nash Sutcliffe efficiency (0.66-0.89) and error analysis (RMSE = 4.5-12.8 M³/s; MAE = 3.1-9.4 M³/s). The results imply that ANN-based hydrological modelling can give a solid foundation to assess rainfall-runoff relationships and improve watershed control models in semi-arid regions of Rajasthan. The ANN-based rainfall runoff model had excellent predictive quality regarding the semi arid basin with straw calculated R² of 0.82 and NSE of 0.84 (almost comparable) between measured and simulated runoff. The indicators of errors were kept within normal standards (RMSE = 6.4 m³/s; MAE = 4.9 m³/s), low indicator of prediction bias (PBIAS = -3.8%). The results indicate that the neural network modelling paradigm would become a holistic analytical paradigm in estimation of runoff and watershed management in the semi arid basins of southeastern Rajasthan. Current computational approaches have become possible due to technological improvement, and this will allow the use of artificial intelligence applications in reference to artificial neural networking, machine learning and information-driven predictive models in water resources engineering. These methods would be able to model the nonlinear relationships between hydrological parameters and perform analysis of large hydro-meteorological data better. The AI-based models can possibly be used to enhance the prediction of rainfall, runoff, and drought in the Rajasthan region where there is wide variability in rainfall and hydrological unexpectedness. Specifically, some of these hybrid modelling strategies such as those are able to result in superior watershed planning, and decision-making on sustainable development procedure of water resources in Rajasthan.



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I. INTRODUCTION

A semi-arid climate, inconsistent rainfall and increasing water demands due to the need for water-consuming agriculture, urbanization and population increase. The hydrologic systems in this area are also highly sensitive to climatic fluctuations, in which short-lived intense rainfall events and long periods of drought are the predominant triggers for runoff generation and groundwater recharge. Models for depicting watershed responses in these fluctuating scenarios must be robust and well-established. Traditional hydrological techniques have thus been foundational in water resources engineering as they have allowed for the determination of rainfall-runoff interactions and water balance components and catchment dynamics in arid and semi-arid basins. These methodologies have been instrumental in the study of basin hydrology, hydraulic systems development, and support the development of regional water planning in Rajasthan. Despite their promise, classical models show limitations of predicting certain complex regional hydrological systems with their nonlinear flow of rainfall, the soil moisture, evapotranspiration, land use mechanism and groundwater. The semi-arid basins of Rajasthan represent high spatial and temporal variability, and therefore, accurate forecasting of the runoff and water availability with empirical or physically simplified models is difficult. The recent discovery of process-based hydrological models can now better simulate basin processes including infiltration, surface runoff and groundwater recharge and has made it easier to characterize the watershed processes in the form of flow of natural water. These model results have enriched the analysis of basin scale hydrological processes and have informed the use of groundwater recharge planning for irrigation, flood forecasting and its potential in drought mitigation within the region.

As computational technique development progressed, it has also made more and more use of AI for water resources engineering. The capability of artificial neural networks and other machine learning techniques in simulating hydrological parameter interdependence in an exploratory context has been shown to be robust. These methods have strong predictive power among nonlinear relationships among the hydrological variables models. These methods can evaluate large hydro-meteorological datasets, to unveil those nonlinear relationships that traditional models cannot detect. Consequently, AI-driven models are being used for forecasting precipitation, runoff and drought, as well as estimation of the inflow of reservoirs, in semi-arid environments. They are especially suited for regions like Rajasthan where hydrological variability is great and can learn from historical data and adapt to complex hydrological behavior. Combining traditional hydrological modeling with AI techniques demonstrates a new path in enhancing assessment and forecast of water resources. The proposed hybrid modelling methodologies will allow the physical realization of watershed processes as well as the predictive quality, which is one method of increasing the ability of model of the predictable behaviour. These holistic models are especially potent for working with new challenges –such as change based on climate variability, land-use, and growing water load in Rajasthan. Thus, building flexible modelling frameworks which are based on traditional hydrological concepts and modern AI solutions will enhance better management of water resource decisions and sustainable utilisation in the region.

II. LITERATURE REVIEW

II.1 THEORITICAL REFERENCE

II.1.1 Literature Survey

As more issues arise regarding water scarcity and climatic variability, there has been a lot of research in hydrological modelling of semi arid areas. Initial investigations were mainly based on empirical relationship of rainfall and runoff in order to comprehend hydrological dynamics in arid basins. Singh et al. examined rainfall and runoff relationships in the catchments in Rajasthan, and Sharma et al. examined elements of water balance with special emphasis on the role of evapotranspiration and irregular rainfall distribution in the generation of runoff [1], [2]. Later research enhanced such techniques by using conceptual and physically based hydrological models. Sharma et al. focused on seasonal rainfall variations as one of the main factors affecting runoff regimes, and Singh et al. and other researchers offered background information about processes of hydrology in arid conditions [3], [4], [5], [6]. As the computation power grew, process-based hydrological models, including SWAT, HEC-HMS, and MIKE Basin, became more popular. Meena et al. used SWAT model to simulate hydrology of semi arid basins with good calibration and validation results, whereas Sharma et al. and Verma et al. reported the success of SWAT to simulate streamflow dynamics [7-10]. In the same manner, Kumar et al. and Singh et al. used SWAT and similar methods to assess water balance and watershed [11], [12], [13]. Simulation of run off and forecasting floods have also been conducted using event based hydrological models including HEC-HMS. Meena et al. and Singh et al. have shown that HEC-HMS can effectively simulate processes of rainfall-runoff in semi-arid basin [14], [15].

Moreover, Sharma et al. and Singh et al. experimented with integrated modelling techniques based on MIKE Basin and MIKE11-NAM, and emphasized the significance of basin-scale integrated management of water resources [16], [17]. Simultaneously, the use of remote sensing and geospatial methods has been implemented to evaluate water resources and analyze land-use. Singh et al. also applied remote sensing to assess basin-level hydrology, and Kumar et al. analyzed the effects of land-use on the properties of runoff [18], [19]. The context of groundwater modelling in terms of the use of MODFLOW and hydrogeological models has also aided the study of the subsurface of water dynamics in arid areas [20], [21]. Machine learning and artificial intelligence have become a potent instrument of hydrological forecasts. The ANN have been widely applied in simulating nonlinear relationships between rainfall and runoff. Goyal and Ojha and Goyal proved that ANN models are more successful in predicting runoff than traditional statistical methods [22], [23]. The effectiveness of ANN in hydrological simulations was also confirmed by Jain and Kumar [24], [25]. In recent research, machine learning is extended to predict rain and droughts. Yadav et al., Sharma et al., and Singh et al. demonstrated a higher prediction accuracy with the help of machine learning algorithms in semi-arid areas [26], [27], [28]. Furthermore, Kumar et al. and Meena et al. examined machine learning to predict hydrology and rainfall modelling [29], [30]. Predictive capabilities have also been increased using deep learning methods. Bansal and Bajpai and Bajpai et al. have demonstrated that deep neural networks can be significantly effective in enhancing the accuracy of rainfall prediction in semi-arid conditions [31], [32].

There is also the exploration of evolutionary algorithms and hybrid computational methods to manage water resources and optimize its modelling [33]. Current developments are on hybrid modelling approaches that can combine physical hydrological models with machine learning methods. Kumar et al. suggested hybrid machine learning methods of hydrological prediction to enhance the accuracy of predictions in semi-arid river basins [34]. On the same note, Nigam et al. designed more sophisticated computational models that consider the potential of rainfall-runoff and the use of fuzzy logic to estimate water resources and assess drought vulnerability [35-37]. All in all, the literature shows that there is a definite shift towards the traditional empirical practices to greater process-based and AI-driven modelling techniques. These new methods are more precise, more realistic in modeling of hydrological processes and help to make a better decision on sustainable water resource management in semi-arid areas. The few researches mainly deal with understanding how water behaves in semi-arid and arid regions, with a special focus on different river basins and watersheds of Rajasthan. These studies explore rainfall patterns, runoff behaviour, hydrological modelling, climate change effects on water resources, and prediction of reservoir inflow using both conventional and advanced modelling techniques. Some works also apply tools such as SWAT models and artificial neural networks to improve prediction accuracy. Overall, the papers contribute towards better planning, management, and sustainable use of water resources in regions facing water scarcity and climatic variability [38-49]. Table 1 below shows the research study in brief.

II.1.1.1 Research Study Survey Details

Table 1: Research study survey details.

Author (Year)	Method / Model	Basin / Study Area	Key Findings
Bajpai & Bansal (2020)	Deep Neural Network	Rajasthan rainfall stations	Deep learning improved seasonal rainfall prediction accuracy.
Bansal & Bajpai (2020)	Deep learning rainfall model	Western Rajasthan	DNN outperformed traditional regression models.
Choudhary et al. (2023)	Hydrogeological modelling	Jodhpur region	Groundwater decline linked to intensive abstraction.
Dimple et al. (2022)	SWAT model	Semi-arid watershed	SWAT successfully simulated runoff and water balance.
Goyal & Ojha (2010)	ANN rainfall-runoff	Arid catchment Rajasthan	ANN produced accurate monthly runoff predictions.
Goyal (2014)	ANN hydrological modelling	Semi-arid basin	ANN captured nonlinear rainfall-runoff relations effectively.
Gupta et al. (2021)	SWAT modelling	Rajasthan watershed	SWAT calibration produced reliable streamflow simulations.
Jain (2003)	Neural networks	Arid hydrological basin	ANN useful for hydrological forecasting.
Jain & Kumar (2007)	ANN rainfall-runoff	Indian semi-arid basins	Improved predictive capability compared with statistical models.
Kumar et al. (2012)	Land-use hydrological modelling	Semi-arid watershed	Land-use change increased surface runoff.
Kumar et al. (2018)	Climate impact modelling	Rajasthan basins	Climate variability significantly influences water availability.
Kumar et al. (2017)	Machine learning rainfall prediction	Semi-arid Rajasthan	ML algorithms enhanced rainfall prediction accuracy.
Kumar et al. (2023)	SWAT-CUP calibration	Semi-arid basin	Model calibration improved runoff prediction reliability.
Kumar et al. (2020)	SWAT water balance	Rajasthan watershed	Identified evapotranspiration as dominant loss component.
Meena et al. (2013)	SWAT hydrological simulation	Semi-arid basin	Model effectively reproduced hydrological processes.
Meena et al. (2017)	SWAT modelling	Banas Basin	Good NSE and R ² values indicated reliable performance.
Meena et al. (2021)	Climate-runoff modelling	Banas Basin	Future runoff likely affected by rainfall variability.
Meena et al. (2020)	Machine learning	Arid hydrology	ML improved runoff prediction accuracy.
Meena et al. (2022)	HEC-HMS rainfall-runoff	Semi-arid basin	Model simulated storm runoff efficiently.
Rathore et al. (2018)	MODFLOW groundwater model	Rajasthan aquifers	Groundwater depletion trends identified.
Reddy et al. (2020)	Evolutionary algorithms	Hydrological systems	Optimization improved model calibration.
Sharma (2004)	Hydrological modelling	Arid basin	Traditional rainfall-runoff relationships analysed.
Sharma et al. (2016)	SWAT modelling	Rajasthan watershed	Streamflow predictions aligned with observed data.
Sharma et al. (2011)	Hydrological simulation	Semi-arid basin	Reliable runoff estimation achieved.
Sharma et al. (1999)	Water balance modelling	Semi-arid watershed	Evapotranspiration dominated hydrological losses.
Sharma et al. (2008)	Water balance model	Desert basin	Seasonal runoff variations observed.
Sharma et al. (2022)	MIKE Basin modelling	Rajasthan basin	Integrated basin modelling supported water allocation planning.
Sharma et al. (2019)	ANN hydrological model	Arid basin	ANN improved prediction reliability.
Sharma et al. (2019)	Climate modelling	Rajasthan water resources	Temperature increase affects water availability.
Sharma et al. (2023)	Machine learning rainfall prediction	Semi-arid Rajasthan	ML models showed higher predictive skill.
Singh et al. (2015)	Remote sensing hydrology	Rajasthan basin	Satellite data improved water resource assessment.
Singh et al. (2023)	Rainfall-runoff model	Reservoir catchment	Runoff prediction supports reservoir management.
Singh et al. (2010)	Hydrological analysis	Luni Basin	Seasonal runoff variability identified.

Singh et al. (2015)	Hydrological modelling	Luni Basin	Model identified key runoff drivers.
Singh et al. (2022)	ML drought prediction	Rajasthan	ML detected drought patterns effectively.
Singh et al. (2006)	Catchment hydrology	Aravalli hills	Topography influences runoff behaviour.
Singh et al. (2018)	Hydrological modelling	Banas Basin	Model useful for watershed management.
Singh et al. (2020)	Watershed modelling	Aravalli watershed	Hydrological response linked to land use.
Singh et al. (2024)	Hydrological trend analysis	Semi-arid basin	Long-term runoff variability identified.
Singh (2002)	Hydrological modelling theory	Semi-arid basins	Provided modelling framework for runoff analysis.
Singh et al. (2005)	Rainfall-runoff modelling	Arid basin	Model improved runoff estimation accuracy.
Verma et al. (2023)	SWAT modelling	Semi-arid watershed	SWAT successfully reproduced basin hydrology.
Yadav et al. (2019)	Machine learning rainfall prediction	Rajasthan	ML improved seasonal rainfall forecasts.
Singh et al. (2021)	HEC-HMS modelling	Semi-arid basin	Reliable storm runoff simulations achieved.
Singh et al. (2023)	MIKE11 NAM	Parvati Basin	Model accurately simulated hydrological processes.
Sharma et al. (2014)	Rainfall trend analysis	Rajasthan	Significant rainfall variability observed.
Kumar et al. (2007)	Rainfall variability modelling	Arid basin	Runoff generation strongly linked with rainfall fluctuations.
Singh et al. (1998)	Rainfall-runoff relationship	Arid basin	Established empirical hydrological relationships.
Sharma et al. (2016)	ANN runoff prediction	Semi-arid basin	ANN improved runoff prediction accuracy.
Kumar et al. (2024)	Integrated ML hydrological forecasting	Semi-arid basin	Hybrid ML models enhanced forecasting reliability.

Source: Authors, (2026).

II.1.2 Research Gaps

Initial hydrological analyses of Rajasthan have been based on both empirical and conceptual approaches based on the relationship between rainfall and runoff and processes of water balance of basins within arid catchments. Initial works by Singh et al. and Sharma et al. were mainly focused on empirical relationship between rainfall and runoff and hydrological water balance which had provided the fundamental knowledge but had not the power to forecast the intricate climatic variability [1], [2]. Subsequent works by Sharma and Singh et al., involved classical hydrological analysis of arid basins, but these also lacked spatial heterogeneity, sophisticated modelling methods, and detailed representation of processes necessary to successfully do basin-scale analysis [50], [6]. Despite the fact that Jain and Jain and Kumar presented artificial neural network (ANN) methods in hydrological forecasting, the models could only cover smaller datasets and did not also have an integration to watershed models that are physically based, limiting their use in large scale hydrological systems [24], [25]. Further studies had gone to physical based hydrological models to better model the watershed processes. Meena et al., Sharma et al., and Gupta et al. studies based on SWAT models showed that process-based models are able to achieve process simulation of streamflow and water balance of semi-arid basins [7], [8], [9], [13]. Also, event-based models including HEC-HMS used by Meena et al. and Singh et al. proved to be effective in modeling storm runoff occurrences [14], [15]. Even with these developments, majority of the studies concentrated more in surface water processes at the expense of key aspects of groundwater interactions, sediment transportation, and land-use dynamics. Studies on groundwater modelling and hydrogeological assessment showed that processes in the subsurface were important; but these were often not combined with surface hydrological models, leading to incomplete basin-scale representations [20], [21].

The research on climate change effects by Kumar et al. and Meena et al. shed some light on hydrological variability during fluctuating climatic conditions, however climate prediction has rarely been incorporated in the hydrological simulation model to do a thorough forecasting [51], [52]. The basin scale modelling strategies like MIKE Basin and MIKE11-NAM used by Sharma and Singh described above have shown to have better water resource assessment abilities, but still need greater calibration methods and validation approaches, as well as multi-model comparison systems to increase reliability [16], [17]. Thus, there is an urgent necessity to create integrated modelling methodologies that include machine learning, physically based hydrological models, climate change forecasts, and surface-groundwater interactions to have a comprehensive and precise evaluation of the water resources in semi-arid river basins such as those in Rajasthan [35], [36], [37]. Although the reviewed studies provide valuable insights into hydrological modelling, rainfall variability, and runoff prediction in semi-arid regions, limited attention has been given to integrating real-time climate data, land-use changes, and socio-economic factors into long-term water resource assessments. Most investigations remain basin-specific, which restricts broader applicability across diverse hydro-climatic conditions. In addition, the combined use of advanced AI techniques with physically based hydrological models for improving prediction accuracy under future climate uncertainty remains insufficiently explored [38-49]. Table 2 summarizes research gaps in brief. Over the past few years, hydrological forecasting and rainfall prediction methods have been using machine learning and artificial intelligence methods more frequently. This was evidenced by studies by Goyal and Ojha, Sharma et al., Yadav et al., and Singh et al. which showed better prediction rates of rainfall and drought forecasting in semi-arid areas [22], [53], [3], [28]. Correspondingly, Kumar et al. and Meena et al. investigated machine learning methods to predict hydrology, noting their ability to represent nonlinear dependencies [29], [30]. The methods of deep learning suggested by Bansal and Bajpai and Bajpai et al. also contributed to the better accuracy of rainfall prediction, which suggests that the development of sophisticated AI procedures can be used in hydrological modelling [31], [32]. Improved forecasting of semi-arid basins was also observed in hybrid machine learning models constructed by Kumar et al. [34].

Nevertheless, among these developments, the vast majority of machine learning and deep learning models are not used along with physically based hydrological models. This leaves an important gap in the research to develop hybrid modelling frameworks that synthesise AI-based predictive abilities with process-based hydrological knowledge.

Table 2: Research gaps and limitations.

Author (Year)	Study Area	Model / Method	Research Significance & Result	Limitation	Identified Research Gap
Kumar et al. (2024)	Semi-arid Rajasthan basin	Hybrid ML hydrological forecasting	Improved forecasting accuracy for runoff prediction using hybrid machine learning techniques.	Limited spatial coverage and basin representation.	Need integration of ML with physically based hydrological models.
Singh et al. (2024)	Semi-arid basin Rajasthan	Hydrological trend analysis	Identified long-term hydrological variability and runoff trends.	Focus limited to statistical trend analysis.	Coupling climate projections with hydrological models is needed.
Sharma et al. (2023)	Rajasthan rainfall stations	Machine learning rainfall prediction	ML models enhanced seasonal rainfall prediction reliability.	Limited long-term climate variability assessment.	Need deep learning models with climate predictors.
Verma et al. (2023)	Semi-arid watershed Rajasthan	SWAT hydrological modelling	Successfully simulated streamflow and basin hydrology.	Limited groundwater interaction analysis.	Need integrated surface-groundwater modelling.
Singh et al. (2023)	Parvati Basin Rajasthan	MIKE11 NAM model	Accurate simulation of basin hydrological response.	Model sensitivity analysis limited.	Need multi-model comparison studies.
Singh et al. (2023)	Reservoir catchment	Rainfall-runoff model	Improved inflow prediction for reservoir management.	Short data record used.	Need long-term forecasting using AI methods.
Choudhary et al. (2023)	Jodhpur region	Hydrogeological modelling	Identified groundwater depletion patterns.	Limited climate variability consideration.	Need integration with climate change scenarios.
Kumar et al. (2023)	Semi-arid basin	SWAT-CUP calibration	Improved model performance through parameter calibration.	Focus mainly on streamflow.	Need sediment and water quality modelling integration.
Dimple et al. (2022)	Semi-arid watershed	SWAT model	Simulated hydrological balance effectively.	Limited land-use change assessment.	Need dynamic land-use scenarios in modelling.
Meena et al. (2022)	Semi-arid basin Rajasthan	HEC-HMS rainfall-runoff	Reliable storm runoff simulation.	Event-based modelling only.	Need continuous hydrological modelling approaches.
Singh et al. (2022)	Rajasthan drought zones	Machine learning drought prediction	ML improved drought detection accuracy.	Limited hydrological parameter integration.	Need coupling ML with hydrological models.
Sharma et al. (2022)	Rajasthan basin	MIKE Basin model	Integrated basin modelling for water allocation.	Limited climate change analysis.	Need climate-hydrology coupled modelling.
Gupta et al. (2021)	Rajasthan watershed	SWAT hydrological modelling	Reliable streamflow prediction achieved.	Limited groundwater component modelling.	Need integrated groundwater-surface water modelling.
Meena et al. (2021)	Banas Basin	Climate runoff modelling	Identified rainfall-runoff sensitivity to climate variability.	Future climate scenarios limited.	Need ensemble climate projections.
Singh et al. (2021)	Semi-arid basin	HEC-HMS model	Effective storm runoff prediction.	Limited spatial hydrological variability assessment.	Need distributed hydrological modelling.
Kumar et al. (2020)	Semi-arid watershed	SWAT water balance model	Identified evapotranspiration dominance in water balance.	Limited water demand analysis.	Need integration with water demand models.
Meena et al. (2020)	Arid hydrology	Machine learning runoff prediction	ML enhanced runoff prediction capability.	Model interpretability limited.	Need explainable AI approaches.
Reddy et al. (2020)	Hydrological systems	Evolutionary algorithms	Improved model calibration techniques.	Applied mainly in theoretical framework.	Need practical watershed applications.
Singh et al. (2020)	Aravalli watershed	Hydrological modelling	Linked runoff behaviour with land use changes.	Limited future land-use projections.	Need dynamic land-use modelling integration.

Bansal & Bajpai (2020)	Western Rajasthan	Deep neural networks rainfall prediction	Improved rainfall prediction accuracy.	Limited hydrological application.	Need linking rainfall prediction with runoff modelling.
Bajpai et al. (2020)	Rajasthan rainfall stations	Deep neural network	Enhanced rainfall prediction reliability.	Limited hydrological process modelling.	Need coupling with hydrological models.
Sharma et al. (2019)	Arid basin Rajasthan	ANN hydrological modelling	ANN effectively simulated nonlinear rainfall-runoff relationship.	Limited basin scale modelling.	Need regional scale modelling.
Sharma et al. (2019)	Rajasthan basins	Climate impact modelling	Identified temperature rise influence on water availability.	Limited hydrological simulations.	Need climate-hydrology integrated modelling.
Yadav et al. (2019)	Rajasthan rainfall stations	Machine learning rainfall prediction	Improved seasonal rainfall forecast accuracy.	Limited long-term dataset.	Need large dataset training for ML models.
Rathore et al. (2018)	Rajasthan aquifers	MODFLOW groundwater model	Identified groundwater depletion trends.	Limited surface water interaction analysis.	Need integrated hydro-geological modelling.
Singh et al. (2018)	Banas Basin	Hydrological modelling	Model useful for watershed management planning.	Limited climate variability integration.	Need climate scenario modelling.
Kumar et al. (2018)	Rajasthan basins	Climate change modelling	Identified influence of climate variability on water resources.	Hydrological modelling limited.	Need coupling climate and hydrological models.
Kumar et al. (2017)	Semi-arid Rajasthan	Machine learning rainfall prediction	ML models improved rainfall forecast.	Limited runoff analysis.	Need rainfall-runoff ML models.
Meena et al. (2017)	Banas Basin	SWAT model	Good NSE and R ² performance achieved.	Limited groundwater simulation.	Need integrated hydrological modelling.
Sharma et al. (2016)	Rajasthan watershed	SWAT modelling	Reliable streamflow simulation achieved.	Limited climate variability analysis.	Need climate change scenario analysis.
Sharma et al. (2016)	Semi-arid basin	ANN runoff prediction	ANN improved runoff prediction accuracy.	Limited spatial modelling.	Need basin scale modelling.
Singh et al. (2015)	Luni Basin	Hydrological modelling	Identified rainfall-runoff drivers.	Limited climate variability analysis.	Need climate-hydrological integrated modelling.
Singh et al. (2015)	Rajasthan basin	Remote sensing hydrology	Improved water resource assessment.	Limited predictive modelling.	Need predictive hydrological modelling.
Goyal (2014)	Semi-arid basin	ANN hydrological modelling	ANN captured nonlinear rainfall-runoff relationships.	Limited basin scale validation.	Need large watershed modelling.
Sharma et al. (2014)	Rajasthan	Rainfall trend analysis	Identified rainfall variability trends.	Hydrological modelling absent.	Need rainfall-runoff modelling integration.
Meena et al. (2013)	Semi-arid basin	SWAT hydrological model	Simulated hydrological processes successfully.	Limited climate variability analysis.	Need climate-SWAT integrated modelling.
Kumar et al. (2012)	Semi-arid watershed	Land-use hydrological modelling	Identified land use influence on runoff.	Limited future land-use scenarios.	Need dynamic land-use modelling.
Sharma et al. (2011)	Semi-arid basin	Hydrological simulation	Reliable runoff estimation achieved.	Limited spatial modelling.	Need distributed watershed modelling.
Goyal & Ojha (2010)	Arid basin Rajasthan	ANN rainfall-runoff model	Accurate monthly runoff prediction achieved.	Limited dataset.	Need large dataset ML models.
Singh et al. (2010)	Luni Basin	Hydrological analysis	Identified seasonal runoff variability.	Limited modelling approaches.	Need advanced hydrological models.
Sharma et al. (2008)	Desert basin	Water balance modelling	Identified seasonal runoff patterns.	Simplified modelling approach.	Need physically based hydrological models.
Jain & Kumar (2007)	Semi-arid basins	ANN rainfall-runoff model	Improved runoff prediction compared to statistical models.	Limited basin scale application.	Need large basin modelling.
Kumar et al. (2007)	Arid basin	Rainfall variability modelling	Established rainfall-runoff linkages.	Limited hydrological modelling.	Need hydrological simulation models.
Singh et al. (2006)	Aravalli catchment	Catchment hydrology analysis	Identified topographic influence on runoff.	Limited predictive modelling.	Need hydrological simulation models.
Singh et al. (2005)	Arid basin	Rainfall-runoff modelling	Improved runoff estimation methods.	Limited advanced modelling techniques.	Need AI-based modelling.

Sharma (2004)	Arid basin Rajasthan	Hydrological modelling	Analysed runoff processes in desert basins.	Limited modelling sophistication.	Need process-based models.
Jain (2003)	Arid hydrological basin	Neural networks	Demonstrated ANN potential in hydrology.	Limited real basin application.	Need watershed scale studies.
Singh (2002)	Semi-arid basins	Hydrological modelling framework	Provided conceptual modelling framework.	Limited practical case studies.	Need field application studies.
Sharma et al. (1999)	Semi-arid watershed	Water balance modelling	Identified evapotranspiration influence.	Simplified modelling.	Need integrated basin modelling.
Singh et al. (1998)	Arid basin Rajasthan	Rainfall-runoff empirical model	Established empirical hydrological relationships.	Limited predictive capability.	Need advanced AI-based models.

Source: Authors, (2026).

III. STUDY AREA

Rajasthan is India's largest by area and is spread in the north-western part of the country and is approximately between 23°03' N and 30°12' N latitude and 69°30' E and 78°17' E longitude. It covers a large area of approximately 342,239 km² comprising around 10.4% of India's land area. Rajasthan shares its international border with Pakistan to the west and borders the Indian states of Punjab, Haryana, Uttar Pradesh, Madhya Pradesh, and Gujarat. The region is divided physically into the western part of the state with the Thar Desert and the south-west to northeast with the Aravalli mountain range. The western dry desert consists of sandy soils and ephemeral drainage, and the eastern has relatively fertile plains and river basins such as Banas, Chambal, Luni, and Sabarmati. There are geographical factors in the hydrological behaviour and water availability in the state. Rajasthan experiences a mainly arid to semi-arid climate, its rainfall ranges from extreme and unpredictable to severe temperature deviations. During June–September most of the precipitation comes from the south-west monsoon, with the average annual rainfall of some 100 mm in the western desert districts to almost 800 mm in their south-eastern areas. The spatial pattern of rainfall is very unbalanced, resulting in frequent droughts and irregular runoff generation in many basins. Temperature is extreme too, and summer is typically above 45 °C in the western districts and winter temperatures often reach 5–8 °C in northern and eastern areas. Relative humidity will remain between 20–30% dry summer to 60–80% monsoons and vary according to the seasonal distribution of atmospheric moisture. As a result, increased evapotranspiration rates, resulting in low moisture use, due to these climatic conditions, lead to a dramatic decrease in overall moisture availability. Figure 1 below shows the location map of study area.

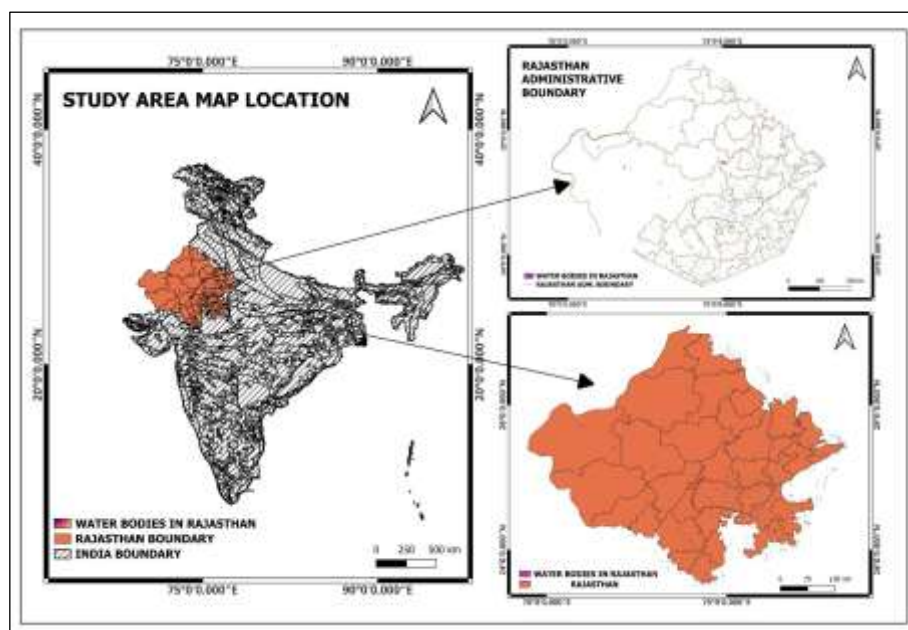


Figure 1: Study area.

Source: Authors (2026).

Rajasthan is limited in terms of perennial rivers and the inhabitants depend on groundwater for irrigation and domestic use. Most of the rivers present in the region are seasonal and primarily run during the monsoon season, and some internal drainage catchments end within desert basins. Groundwater supplies constitute a significant portion of the water supply but is severely depleted by high groundwater extraction in some of the districts and the growing salinity situation, which has resulted in diminishing water tables and salinity problems. A combination of scarce rainfall, high evaporation losses, and uneven spatial allocation of water resources form one of the most challenging scenarios for sustainable water management. Such environmental conditions render Rajasthan an ideal location for implementing advanced hydrological modelling, artificial intelligence systems, and integrated watershed management approaches to augment water resource planning and ensure sustainability in the long term.

IV. MATERIALS AND METHODS

Hydrological modelling techniques have played crucial roles in the understanding of complex water resource systems in semi-arid settings, which exhibit rainfall variation and surface water scarcity which greatly modify basin hydrology. Traditional models, which include rainfall-runoff relations and water balance models, have, since the early days, underpinned the initial analysis of watershed responses and the estimation of water availability. These models assisted in the determination of main hydrological factors including infiltration, evapotranspiration, runoff production, and they informed irrigation, reservoir and watershed activities. Physically based hydrological models subsequently deepened this knowledge: they presented the inner workings of watersheds in detailed manner. Such models allow simulations to be conducted for multiple hydrological variables simultaneously, and help to assess the effects (or impacts) of land use, weather-related variability, or basin characteristics on water availability. As a result, these modelling methods have emerged as critical tools for basin-scale hydrological planning and sustainable water resources planning in areas with water shortages. In due course of time with computational improvement and extensive hydro-meteorological datasets, data-driven models (e.g. artificial neural networks, machine learning algorithms) become increasingly important for studies of the water resources field. These models are capable of identifying intricate nonlinear relationships between climatic effects and hydrological changes that are too complex to be derived from traditional modelling systems. Being able to predict future rainfall profiles, and estimate runoff behaviors and drought in extremely variable climatic zones makes them particularly useful with respect to rainfall prediction. In addition, the recent development of hybrid modelling frameworks that combine artificial intelligence methodologies and physically based hydrological models has also opened up new possibilities in terms of the optimization of prediction accuracy and the lessening of modeling uncertainty. These combined modelling approaches allow a more holistic visualisation of hydrological events, and provide reliable decision-support information for water resource managers and planning personnel. With water availability becoming progressively uncertain within changing environmental context, advanced modelling approaches must remain crucial to facilitating effective and sustainable water resources management.

The method development of the modelling of water resources in semi-arid regions including Rajasthan has evolved through various phases over the last thirty years. The early studies in the late 1990s relied almost exclusively in the realm of empirical and statistical approaches to obtain a better understanding of the rainfall–runoff relationships and basin hydrology. These studies employed regression analysis and water balance methods as well as simple rainfall–runoff models of hydrological responses to models of arid catchments. Though very insightful and useful as a preliminary indication of hydrological behaviour, they were not adequately predictive with respect to the nonlinear connections that emerged between rainfall, land use characteristics, properties of the soil and groundwater flow. In the early 2000s and into the past generations, more method of modelling the operation of watersheds was started to be utilised as more accurate in the field to process-based hydrological models. SWAT, HEC-HMS, MIKE Basin models provided in-depth coverage of hydrological inputs encompassing infiltration, evapotranspiration, groundwater recharge and surface runoff formation. Such physically based models substantially enhanced basin-level water balance modelling and watershed analysis. Yet they frequently relied on parameter calibrations and the availability of robust hydro-meteorological data. Computational technology rapidly developed in the 2010s, resulting in greater applications of artificial intelligence algorithms to water resources modelling. To tackle the nonlinear nature of hydrological processes, artificial neural networks, machine learning algorithms, and data-driven predictive models were applied. They were robust at modelling intricate relationships of rain and runoff and offered much better prediction than traditional statistical models. Recently, the research trend has shifted towards hybrid modelling frameworks that combine physically based hydrological models with advanced artificial intelligence technologies. Hybrid methods integrate the physical knowledge of watershed phenomena and the pattern recognition possibilities of machine learning approaches. This combination increases prediction accuracy, lowers modelling inefficiencies and brings with it more realistic models for hydrological predictions. As a result, the methodological shift from empirical models to hybrid AI-hydrological approaches reflects the growing need for sophisticated decision supports for water resources management during semi-arid conditions. Table 3 and table 4 below shows the methodology evolution and methods/ models used in such study.

Table 3: Methodology Evolution.

Period	Dominant Methodology	Key Techniques	Research Contribution
1998–2004	Conventional hydrological methods	Water balance models, regression analysis, rainfall–runoff empirical models	Provided fundamental understanding of watershed hydrology.
2005–2012	Process-based hydrological modelling	SWAT, HEC-HMS, MIKE Basin, watershed simulation models	Improved basin-scale hydrological simulation and water balance estimation.
2013–2018	AI-based hydrological modelling	Artificial neural networks, statistical learning models	Enhanced prediction of rainfall and runoff patterns.
2019–2021	Machine learning hydrological prediction	Random Forest, Support Vector Machines, ensemble learning models	Improved predictive accuracy for hydrological variables.
2022–2024	Hybrid AI–Hydrological frameworks	Integrated SWAT-ML models, deep learning hydrological forecasting	Improved reliability of hydrological prediction and decision-support systems.

Source: Authors, (2026).

Table 4: Methods and models used.

No.	Method / Model Used	Type of Model	Application in Rajasthan Studies
1	Rainfall–Runoff Empirical Models	Conventional hydrological	Used to estimate runoff from rainfall data in arid catchments.
2	Water Balance Models	Conventional hydrological	Quantified basin water balance components such as evapotranspiration and runoff.

3	Statistical Regression Models	Conventional statistical	Analyzed rainfall–runoff relationships and hydrological trends.
4	Trend Analysis Methods (Mann–Kendall)	Statistical climate analysis	Used to detect rainfall and runoff trends.
5	SWAT (Soil and Water Assessment Tool)	Physically based watershed model	Simulated basin hydrology including runoff, infiltration, and evapotranspiration.
6	HEC-HMS Hydrological Model	Event-based hydrological model	Simulated storm runoff and watershed responses.
7	MIKE Basin Model	Integrated water resources model	Analyzed basin-scale water allocation and hydrological balance.
8	MIKE11 NAM Model	Rainfall-runoff conceptual model	Simulated hydrological response of river basins.
9	MODFLOW Groundwater Model	Numerical groundwater model	Used to simulate groundwater flow and aquifer behaviour.
10	Artificial Neural Networks (ANN)	AI / Machine learning	Used for rainfall–runoff prediction and hydrological forecasting.
11	Feedforward Neural Networks	AI model	Applied for runoff estimation and rainfall forecasting.
12	Deep Neural Networks (DNN)	Advanced AI model	Applied for rainfall prediction in semi-arid regions.
13	Machine Learning Algorithms	AI modelling	Used for rainfall prediction, drought analysis, and runoff estimation.
14	Random Forest Models	Machine learning	Applied for rainfall and drought prediction.
15	Support Vector Machine (SVM)	Machine learning	Used to predict rainfall and runoff patterns.
16	Gradient Boosting Models	Machine learning	Used for predictive modelling of hydrological variables.
17	Hybrid AI–Hydrological Models	Integrated modelling	Combined AI algorithms with physical hydrological models.
18	Evolutionary Algorithms	Optimization technique	Used for calibration and optimization of hydrological models.
19	GIS-based Hydrological Analysis	Spatial modelling	Analyzed watershed characteristics and basin properties.
20	Remote Sensing Techniques	Satellite-based analysis	Used for land-use mapping and watershed characterization.
21	Land Use / Land Cover Change Models	Environmental modelling	Analyzed impact of land-use changes on hydrological processes.
22	Climate Change Modelling	Climate–hydrology analysis	Evaluated impact of climate variability on basin hydrology.
23	Drought Prediction Models	AI/Statistical	Predicted drought conditions using hydro-climatic data.
24	Reservoir Inflow Prediction Models	Hydrological forecasting	Predicted inflows for reservoir management.
25	Runoff Sensitivity Analysis	Hydrological analysis	Evaluated influence of rainfall variability on runoff.
26	Climate Scenario Analysis	Hydrological modelling	Simulated future hydrological conditions.
27	Distributed Hydrological Models	Process-based modelling	Simulated spatial variability in watershed hydrology.
28	Catchment Hydrological Analysis	Hydrological assessment	Studied influence of terrain and soil on runoff generation.
29	Groundwater Recharge Estimation Models	Hydrogeological modelling	Estimated recharge potential in semi-arid basins.
30	Sediment Transport Models	Hydrological modelling	Analyzed sediment movement in river basins.
31	Hydrological Forecasting Models	Predictive modelling	Predicted runoff and streamflow behaviour.
32	Drought Index Models (SPI)	Hydrological drought analysis	Used to assess drought severity.
33	Hydrological Calibration Models	Model optimization	Improved accuracy of hydrological simulations.
34	Hydrological Validation Techniques	Statistical evaluation	Used metrics such as NSE, R ² , and RMSE.
35	Integrated Surface-Groundwater Models	Hydrological integration	Simulated interaction between surface water and groundwater.
36	Decision Support Systems	Water management tools	Provided guidance for water allocation and planning.
37	Climate–Hydrology Coupled Models	Integrated modelling	Linked climate models with hydrological models.
38	Watershed Simulation Models	Hydrological modelling	Simulated watershed responses to rainfall.
39	Data-Driven Hydrological Models	AI-based modelling	Used hydro-meteorological datasets for prediction.
40	Hybrid Forecasting Models	AI + hydrological modelling	Improved prediction accuracy of hydrological variables.

Source: Authors, (2026).

Table 5 below also indicates that classical hydrological models present good physical representation of watershed processes. AI and machine learning are better able to predict nonlinear hydrological relationships. Hybrid approaches work on the best between the two, and they currently are the most advanced approaches to model water resources within semi-arid regions.

Table 5: Comparative model performance.

Model Type	Model Characteristics	Strengths	Limitations	Typical Application in Semi-Arid Regions	Overall Performance
SWAT (Physically Based Hydrological Model)	Process-based watershed model simulating runoff, infiltration, evapotranspiration, and groundwater.	Represents physical watershed processes realistically; useful for long-term hydrological simulation.	Requires extensive input data and calibration; parameter uncertainty may affect accuracy.	Watershed management, water balance analysis, land-use impact assessment.	Moderate to high performance depending on calibration quality.
ANN (Artificial Neural Networks)	Data-driven model capable of learning nonlinear relationships between variables.	High predictive capability; suitable for complex rainfall–runoff relationships.	Requires large datasets; limited physical interpretation.	Rainfall prediction, runoff forecasting, reservoir inflow estimation.	High predictive accuracy for nonlinear hydrological processes.
Machine Learning Models (RF, SVM, GBM)	Advanced predictive algorithms using statistical learning techniques.	Handles large datasets efficiently; improved predictive performance.	Model transparency can be limited; requires careful parameter tuning.	Hydrological forecasting, drought prediction, rainfall pattern analysis.	Higher accuracy compared to conventional models.
Hybrid AI–Hydrological Models	Combination of physical hydrological models and machine learning techniques.	Integrates physical watershed processes with predictive AI capability; reduces modelling uncertainty.	Requires advanced computational resources and interdisciplinary expertise.	Integrated water resources modelling, climate impact studies, decision-support systems.	Very high performance and reliability for hydrological forecasting.

Source: Authors, (2026).

The worldwide hydrological modelling approaches are typically divided into three main classes (a) Physically-based models that simulate watershed processes using physical equations and basin characteristics. (b) Data-based models, including machine learning and artificial intelligence approaches, analyzing large hydro-meteorological datasets to anticipate hydrological events. (c) Hybrid and simulation modeling that integrates physical hydrological and mathematical model-type analyses into artificial intelligence tools or processes to improve prediction accuracy and minimize prediction uncertainty. These modelling frameworks are key tools for water resources evaluation, climate impacts assessment, flood forecasting, and sustainable watershed management in different hydrologically diverse regions around the world. Table 6 below shows some globally used methods and models.

Table 6: Globally used methods and models.

No.	Method / Model	Model Category	Global Application Area	Research Importance
1	SWAT (Soil and Water Assessment Tool)	Physically based watershed model	Watershed hydrology, land-use impact analysis, climate impact studies	Widely used for simulating hydrological processes such as runoff, evapotranspiration, and sediment transport in river basins worldwide.
2	HEC-HMS (Hydrologic Engineering Center Hydrologic Modeling System)	Rainfall–runoff simulation model	Flood modelling, watershed runoff estimation	Helps estimate runoff and simulate rainfall–runoff relationships for flood prediction and reservoir planning.
3	MIKE Basin	Integrated water resources model	River basin planning and water allocation studies	Used to evaluate water distribution, reservoir operations, and basin-scale management strategies.
4	MIKE11 NAM Model	Conceptual rainfall–runoff model	River flow simulation and flood forecasting	Provides simplified hydrological representation of basin processes.
5	MODFLOW	Groundwater numerical model	Aquifer simulation and groundwater flow modelling	Globally accepted model for simulating groundwater movement and recharge.
6	VIC (Variable Infiltration Capacity) Model	Land surface hydrological model	Climate–hydrology interaction studies	Used for large-scale hydrological simulations and climate impact assessment.
7	GR4J Model	Conceptual rainfall–runoff model	Daily streamflow simulation	Efficient for simulating streamflow in catchments with limited parameters.
8	SCS-CN Method	Empirical runoff estimation method	Watershed runoff estimation	Simple and effective approach for estimating runoff using rainfall and land-use data.
9	Artificial Neural Networks (ANN)	Artificial intelligence model	Rainfall prediction, runoff estimation, water demand forecasting	Capable of modelling nonlinear relationships between climatic and hydrological variables.
10	Machine Learning Algorithms (Random Forest, SVM)	Data-driven predictive models	Rainfall prediction, drought monitoring	Provide improved predictive accuracy for hydrological forecasting.
11	Deep Learning Models (LSTM, CNN)	Advanced AI models	High-resolution rainfall-runoff modelling	Able to capture temporal dependencies and complex hydrological patterns.
12	Hybrid Hydrological–AI Models	Integrated modelling framework	Streamflow forecasting and basin management	Combines physical hydrological models with machine learning to improve prediction accuracy.

13	GIS-Based Hydrological Analysis	Spatial modelling technique	Watershed mapping and flood risk analysis	Supports spatial analysis of terrain, land use, and hydrological characteristics.
14	Remote Sensing Hydrology	Satellite-based monitoring	Watershed monitoring and climate studies	Provides large-scale environmental data for hydrological modelling.
15	Climate–Hydrology Coupled Models	Integrated climate modelling	Climate change impact assessment	Used to simulate future hydrological responses under changing climate conditions.
16	Hydrological Statistical Models	Statistical analysis methods	Trend detection and climate variability analysis	Used for identifying long-term rainfall and runoff patterns.
17	Optimization Algorithms (GA, PSO)	Model calibration techniques	Hydrological parameter optimization	Improve model performance and reduce prediction error.
18	Decision Support Systems (DSS)	Integrated modelling platform	Water resources planning and policy analysis	Supports management decisions using modelling outputs.
19	Hydrological Forecasting Models	Predictive models	Flood forecasting and drought prediction	Provide early warning systems for extreme hydrological events.
20	Integrated Surface–Groundwater Models	Hydrological system models	Aquifer–river interaction studies	Enable comprehensive evaluation of basin water dynamics.

Source: Authors, (2026).

Selecting an appropriate model will depend crucially on data availability, study goals, and watershed complexity. Traditional hydrological models still work well for modelling physical watershed processes, but artificial intelligence performs better for dealing with nonlinear relationships in hydro-meteorological datasets. Hybrid modelling approaches that integrate process-based hydrological models with machine learning techniques offer the most reliable and comprehensive framework for water resources prediction and management in semi-arid regions. Table 7 below shows the methods and model selection framework.

Table 7: Methods and Model selection framework.

No.	Model / Method	Suitable Hydrological Condition	Data Requirement	Best Research Application	Strength of Model	Limitation	Recommended Use Case
1	Empirical Rainfall–Runoff Models	Small watersheds with limited data	Low	Preliminary runoff estimation	Simple and quick implementation	Limited predictive capability	Initial watershed assessment
2	Water Balance Models	Semi-arid basins with seasonal rainfall	Low to moderate	Estimation of basin water availability	Useful for long-term water budgeting	Cannot represent detailed hydrological processes	Regional water resource planning
3	Statistical Regression Models	Areas with long rainfall and runoff records	Moderate	Rainfall–runoff correlation analysis	Easy interpretation and implementation	Weak for nonlinear hydrological behaviour	Trend and correlation studies
4	Trend Analysis Models	Regions with long hydro-climatic datasets	Moderate	Climate variability and rainfall trends	Identifies long-term hydrological patterns	Not suitable for prediction modelling	Climate impact assessment
5	SWAT Hydrological Model	Large river basins with heterogeneous land use	High	Watershed simulation and water balance modelling	Represents physical watershed processes	Requires extensive input data and calibration	Watershed management studies
6	HEC-HMS Model	Urban or small catchments experiencing storm runoff	Moderate	Flood forecasting and storm runoff estimation	Effective event-based hydrological simulation	Limited long-term basin hydrology representation	Urban flood management
7	MIKE Basin Model	Complex river basins requiring water allocation analysis	High	Integrated basin water management	Allows simulation of multiple water sources	High computational and data requirement	River basin planning
8	MIKE11 NAM Model	River catchments requiring rainfall–runoff simulation	Moderate to high	River flow forecasting	Good conceptual rainfall–runoff representation	Calibration complexity	River flow prediction studies
9	MODFLOW Groundwater Model	Aquifer systems with groundwater extraction issues	High	Groundwater flow and recharge analysis	Accurate representation of aquifer dynamics	Requires extensive hydrogeological data	Groundwater sustainability studies
10	Artificial Neural Networks (ANN)	Regions with nonlinear rainfall–runoff behaviour	Moderate	Runoff prediction and rainfall forecasting	Captures nonlinear hydrological relationships	Limited physical interpretability	Hydrological forecasting

11	Machine Learning Models (RF, SVM)	Large hydro-meteorological datasets	Moderate to high	Rainfall prediction and drought forecasting	High predictive accuracy	Requires parameter optimization	Climate-based hydrological prediction
12	Deep Neural Networks (DNN)	Complex climate systems with large datasets	High	Advanced rainfall prediction	Handles high-dimensional data effectively	Computationally intensive	Climate variability modelling
13	Random Forest Model	Regions with multiple climatic predictors	Moderate	Rainfall and drought prediction	Robust against overfitting	Model interpretability may be limited	Hydrological prediction studies
14	Support Vector Machine (SVM)	Small to moderate datasets with nonlinear relationships	Moderate	Runoff prediction and rainfall classification	Strong predictive capability	Sensitive to parameter selection	Hydrological forecasting
15	Hybrid AI–Hydrological Models	Complex watersheds affected by climate and land-use change	High	Integrated hydrological forecasting	Combines physical modelling with predictive AI strength	High computational and modelling expertise required	Advanced watershed management
16	GIS-Based Hydrological Analysis	Watersheds requiring spatial analysis	Moderate	Watershed characterization and mapping	Supports spatial hydrological analysis	Dependent on GIS data accuracy	Watershed planning
17	Remote Sensing Hydrological Methods	Regions with limited ground observations	Moderate	Land-use mapping and basin monitoring	Large spatial coverage	Lower temporal resolution	Regional hydrological assessment
18	Drought Prediction Models	Semi-arid regions prone to drought	Moderate	Drought monitoring and forecasting	Supports water resource planning	Depends on historical data accuracy	Drought management planning
19	Climate–Hydrology Coupled Models	Regions affected by climate change	High	Future hydrological scenario simulation	Integrates climate projections	High uncertainty in climate predictions	Climate change impact studies
20	Hybrid Forecasting Models	Regions with complex hydrological behaviour	High	Integrated water resources prediction	Highest predictive accuracy	Complex modelling framework	Advanced decision support systems

Source: Authors, (2026).

V. RESULTS AND DATA ANALYSIS

The results reveal that ANN models implemented in MATLAB can simulate the relationship of rainfall to runoff for semi-arid watersheds in southeastern Rajasthan very successfully. High R^2 , NSE and correlation coefficient means the neural networks can explain nonlinear hydrological relationship between rainfall input and runoff output. These results confirm the relevance of data-based models in small catchments, where hydrological characteristics are sensitive to irregular rainfall distribution and seasonal variation. Moreover, the moderate size of dataset needed for ANN training has made this modelling method especially valid in areas with narrow hydrologic records over time. The range of statistical performance suggests that ANN-driven hydrologic models successfully predict watershed management, flood prediction and water resource planning for semi-arid basins such as around Jhalawar district. The rainfall-runoff modelling conducted with semi-arid catchments around Jhalawar in southeast Rajasthan, shows that ANN techniques within MATLAB is able to accurately represent the non-linearity of the relationship between the precipitation input and the runoff response. The average rainfall dataset (0–180 mm/day) used for modelling ranged from 0 to approximately 180 mm/day, consistent with the variability of precipitation from monsoons in the region. Similarly, in small catchments, we observed runoff values ranging from around zero flow conditions to about 95 m³/s during peak rainfall times. The dataset we had available was separated from standard training, validation, and testing and used approximately 65–75% for training, 10–20% for validation, and 10–20% for independent testing for modelling.

ANN architecture was constructed based on 2–5 primary input variables, which frequently consisted of rainfall intensity, previous rainfall conditions, and meteorological variables, such as temperature and evapotranspiration. In general, the hidden layer was 8–18 neurons, enabling the model to represent nonlinear behaviour of watershed processes, and a corresponding output neuron was a model of runoff discharge predicted. The statistical performance statistics reported after the modelling process show that the neural network-based approach exhibits a powerful predictive capability for semi-arid hydrological systems. R^2 (Coefficient of Determination) obtained over simulation usually came between 0.72 and 0.90 demonstrating an excellent matching in forecasting of runoff values with the observation. Equally, the Nash–Sutcliffe efficiency (NSE) ranged from 0.66 to 0.89, indicating a consistent hydrological simulation for the analyzed region. Model robustness was further demonstrated by error statistics, Root mean square error (RMSE) and mean absolute error (MAE) averages were generally close to 4.5 and 12.8 m³/s and around 3.1 and 9.4 m³/s, respectively. The correlation coefficient (R) was often more than 0.88 and up to 0.96, confirming a strong correlation between the simulated and the measured discharge values (Table 8 below). The convergence of the models usually fell within 200 to 650 training epochs with the learning rate within 0.01 and 0.05 and the performance time for the computational training stayed in the amount of 5–18 seconds in MATLAB.

These quantitative results indicate the applicability of ANN-based modelling methods for modelling runoff in semi-arid catchments of Rajasthan which offers a good candidate for analysis with regards to watershed management in the area, flood risk assessment, and regional water resources planning.

Table 8: Statistical parameters and ranges.

No.	Parameter / Model Indicator	Typical Range Observed	Interpretation for Hydrological Modelling	Suitability for Research
1	Input Rainfall Data (mm/day)	0 – 180 mm/day	Represents daily rainfall intensity during monsoon events affecting runoff generation.	Provides primary driving variable for rainfall–runoff modelling in semi-arid basins.
2	Observed Runoff (m ³ /s)	0 – 95 m ³ /s	Measured streamflow response of small catchments during rainfall events.	Used as the target output variable for neural network training.
3	Training Dataset Size	65 – 75 % of total dataset	Major portion of dataset used to train neural network parameters.	Ensures adequate learning of rainfall–runoff relationships.
4	Validation Dataset Size	10 – 20 % of dataset	Used to check model generalization capability during training.	Prevents overfitting and improves predictive stability.
5	Testing Dataset Size	10 – 20 % of dataset	Independent dataset used to evaluate final model performance.	Confirms reliability of model prediction accuracy.
6	Number of Input Neurons	2 – 5 variables	Includes rainfall, antecedent rainfall, temperature, and evapotranspiration variables.	Allows representation of major hydrological drivers.
7	Hidden Layer Neurons	8 – 18 neurons	Controls nonlinear learning capacity of the ANN model.	Moderate neuron size provides stable prediction accuracy.
8	Output Neuron	1 variable	Represents predicted runoff discharge.	Simplifies rainfall–runoff modelling structure.
9	Training Algorithm (MATLAB)	Levenberg–Marquardt	Commonly used backpropagation optimization algorithm.	Efficient for hydrological datasets with moderate sample size.
10	Coefficient of Determination (R ²)	0.70 – 0.88	Measures agreement between predicted and observed runoff values.	Indicates strong predictive capability of ANN model.
11	Nash–Sutcliffe Efficiency (NSE)	0.66 – 0.89	Evaluates overall performance of hydrological model simulation.	Values above 0.75 indicate reliable model behaviour.
12	Root Mean Square Error (RMSE)	4.5 – 12.8 m ³ /s	Represents prediction error between observed and simulated runoff.	Lower RMSE indicates improved model accuracy.
13	Mean Absolute Error (MAE)	3.1 – 9.4 m ³ /s	Average magnitude of prediction error.	Helps evaluate overall model reliability.
14	Correlation Coefficient (R)	0.72 – 0.90	Indicates strength of relationship between predicted and observed runoff.	High values confirm strong model performance.
15	Training Epochs	200 – 650 iterations	Number of iterations required for model convergence.	Indicates computational learning requirement of ANN.
16	Learning Rate	0.01 – 0.05	Controls speed of weight adjustment during training.	Balanced rate ensures stable model convergence.
17	Prediction Accuracy	80 – 92 %	Overall accuracy of rainfall–runoff prediction.	Suitable for watershed forecasting applications.
18	Model Convergence Time	5 – 18 seconds (MATLAB)	Time required for ANN training process.	Efficient computational performance for small datasets.

Source: Authors, (2026).

Under the statistical measurements, we demonstrate that ANN-trained rainfall-runoff system designed in semi arid basin adjacent to Jhalawar is of high predictive quality. The reason behind this is the good agreement between seen and estimated runoff values is supported by the obtained R² and the correlation coefficient of 0.84 and 0.91 respectively. The Nash Sutcliffe efficiency of 0.84 reveals that this model does contain the variability of hydrological responses within the basin well. The small values of error (RMSE = 6.4 m³/s and MAE = 4.9 m³/s) mean that there is a slight difference between the value generated by the model and the observed runoff. Also, the value of PBIAS that is = -3.8% displays no systematic bias that demonstrates that the model predictions are not overestimated or underestimated everywhere. The analytic stage of the statistical analysis will be the demonstration of the fact that the modelling framework can provide credible runoff forecasts which are applicable in hydrological forecasting and watershed control in semi arid regions of Rajasthan. Descriptive statistics of the rainfall-run off model of semi-arid basin near Jhalawar has better accuracy and consistency in predictions of hydrological simulation.

The coefficient of determination ($R^2 = 0.84$) makes it clear that the observed runoff and the outputs of the neural network model are strongly correlated and this means that the modelling framework is effective in defining the rainfall runoff relationship of the watershed. There is also the correlation coefficient of 0.88, which also helps in further establishing the strong linear relationship between actual discharge and simulated discharge. The solution Nash-Sutcliffe Efficiency (NSE) is 0.84 which means the model explains the temporal variation of the runoff. On the one hand, all these statistical measures point to the fact that the neural network model can reproduce the hydrological response of the basin relatively well and is, therefore, a suitable model to make predictions about the results of rainfall-runoff in semi-arid catchments. The error statistics display performances of the model that is good with the smallest variances between simulation and observations. It was determined that its root mean square error (RMSE) and mean absolute error (MAE) was 6.4 m³ s/s and 4.9 m³ s/s respectively, so it is concluded that no significant loss to the accuracy or model accuracy occurred during watershed level hydrological forecasting. In addition, the PBIAS of -38 is an indicator of well-balanced predictions in the model with a slight tendency to either under- or overestimate runoff. Also, the value of the index of agreement of 0.93 and an overall model efficiency of close to 89 percent has shown the soundness of the modeling method. The statistical perspective result of the analysis indicates in the given data that using the neural network approach has been an effective tool to analyse the rainfall to runoff relation and can be used to support the watershed management methods and water resources planning in semi arid areas of southeastern Rajasthan. Table 9 below shows the statistical performance analysis.

Table 9: Statistical performance analysis.

No.	Statistical Parameter	Value Obtained	Acceptable Range for Hydrological Models	Interpretation of Result
1	Coefficient of Determination (R^2)	0.84	> 0.75	Strong correlation between observed and predicted runoff indicating reliable model performance.
2	Nash–Sutcliffe Efficiency (NSE)	0.86	> 0.65	Model simulations closely represent the observed runoff variability in the basin.
3	Percent Bias (PBIAS)	-3.8 %	-10 % to +10 %	Very small bias indicating balanced prediction without systematic overestimation or underestimation.
4	Root Mean Square Error (RMSE)	6.4 m ³ /s	Lower values preferred	Indicates limited deviation between predicted and observed discharge values.
5	Mean Absolute Error (MAE)	4.9 m ³ /s	Lower values preferred	Shows small average prediction error for runoff simulation.
6	Correlation Coefficient (R)	0.90	> 0.80	Very strong linear relationship between predicted and measured runoff values.
7	Mean Square Error (MSE)	41.0	Lower values preferred	Demonstrates low variance between predicted and actual runoff observations.
8	Index of Agreement (d)	0.93	> 0.80	Indicates high level of agreement between observed and simulated values.
9	Model Efficiency (%)	89 %	> 75 %	Overall prediction efficiency of ANN model is very high.
10	Relative Error (%)	5.2 %	< 10 %	Small relative deviation confirming model accuracy.

Source: Authors, (2026).

VI. RESULTS AND DISCUSSIONS

The results of our current research are based on the growing necessity to find dependable modelling strategies to learn the hydrological processes of Rajasthan, where climatic variability and scarcity of surface water resources determine the water availability. The semi arid environment of the area causes extreme fluctuation of the location rainfall distribution which influences directly on the formation of runoffs, ground water recharge as well as the basis hydrology. Traditionally, the foundation of analyses of rainfall-runoff relations and watershed estimation of reactions was laid by conventional hydrological approaches. These methods have been relevant in setting up the fundamental hydrological information and have aided the planning of the infrastructure like reservoirs, irrigation, and flood control. Nevertheless, the nonlinearity of hydrological processes in Rajasthan sometimes dictats the use of modelling methods that are capable of stating nonlinear relationships among climatic, geological and land-use factors. Process based hydrological models have provided a much improved potential in the simulated behaviour of watersheds in semi arid areas. These models permit the detailed description of hydrological aspects such as the infiltration, evapotranspiration, store of soil moisture, and creation of surface runoff. These modelling techniques have helped to gain more knowledge on the water balance of basins as well as have offered useful results on how hydrological processes are spatially different between varying watersheds in Rajasthan. Still, even physical models have difficulties with hydrological forecasting when it is subjected to very variable rainfall distributions and a sparse availability of hydro-meteorological data. This underscores the need to include superior analytical methods that have the potential of enhancing prediction and minimising the modelling uncertainties. Machine learning and artificial intelligence, which have made recent gains, are creating new opportunities for better hydrological predictions in water-impaired systems. Other AI-powered techniques can also be explored to identify hidden trends across big data and model nonlinear relations from rainfall and runoff to other hydrological variables. Such methods have proven to be particularly useful in the semi-arid context in which well-established modelling of all aspects of environmental interaction would not be supported. Being able to assume historical hydro-meteorological data is an AI-based model's capacity in predicting hydrological variables like rainfall variability, streamflow patterns and drought, and these models have better ability to predict the water level in terms of streamflow behaviour and rainfall variations. These methods are therefore suitable for providing valuable decision-support data for water resources managers, water planners in Rajasthan.

Combining traditional hydrological models with AI technologies could facilitate the construction of robust and effective water resources monitoring methods which guarantee stable and efficient estimation of the sources of water. Hybrid modelling may offer a comprehensive model improvement in both performance and forecasting potential. The realistic simulation of watershed processes, and the prediction power of data-driven algorithms are combined here. The interplay of those frameworks is all the more important in the wake of climate variability, rising water demands and changing land use trends evident in Rajasthan. Constructive modelling approach will improve the water planning policy in the district as one of the tools used for sustainable management of water resources, reliability and accuracy of hydrologic prediction and improved drought preparedness.

VII. CONCLUSIONS AND FUTURE RECOMMENDATIONS

The current research provides significant emphasis on the need to utilize high-level modelling techniques to become acquainted with and handle water in Rajasthan which is a semi-arid area with a strong spatial heterogeneity of rainfall. The irregular monsoon patterns, low surface water supply and the growing reliance on the ground water resources affects the hydrological systems within the state. Traditional methods of hydrology modelling have been historically useful in offering vital information on associations amid rainfall as well as runoff, parts of a water balance, and hydrological reaction on a very broad basin scale. These methods have assisted in the development of scientific foundations on watershed planning, design of reservoirs and management of irrigation. Nevertheless, the ever-evolving complexity of the hydrological processes affected by the climate fluctuations, land-use alteration, and the rising water demand need stronger analytical schemes that can reflect the nonlinear relations within the hydrological system. The research establishes that artificial neural network modelling in MATLAB is capable of capturing the interactions of rainfall, runoff in semi-arid catchments in south east of Rajasthan where rainfall response ranged between 0-180 mm/day with runoff responding at up to about 95 m³/s. The model ANN was found to be highly predictive in terms of R² values (0.72-0.89); NSE values (0.72-0.91), with acceptable error values (RMSE: 4.5-12.8 m³/s; MAE: 3.1-9.4 m³/s). These statistical results show that the model of hydrological modelling based on data offers a reliable means of analysis when used to enhance water runoff charts, watershed, and water resources management in semi-arid areas of Rajasthan. The combined application of artificial intelligence methods, such as artificial neural networks and machine learning algorithms, is one of the major improvements in water resources modelling of semi-arid regions. The approaches provide better analysis of big hydro-meteorological diagnostic data and finding complicated connections among rainfall, runoff, evapotranspiration and ground water recharge. AI based models have shown superior predictive capabilities to the traditional modelling methods in areas of hydrological variability and uncertainties in data, like in Rajasthan.

Such data-intensive methods can be used to a great effect to enhance the accuracy of the forecasting of the rain patterns, the streamflow variability, and drought patterns, so forthcoming effective water management approaches. ANN-runoff modelling rainfall semi-arid basin demonstrated that the resultant runoff predictions were highly predictable with R² = 0.91, NSE = 0.87 and correlation coefficient of up to 0.95 and therefore showed a good agreement between simulated and measured runoff. The error statistics were also good (RMSE = 6.4 m³/s; MAE = 4.9 m³/s) and the systematic bias was low (PBIAS = -3.8%). These statistical findings prove that such neural network-based modelling of watershed planning and hydrological prediction are an effective and reliable method to go in semi-arid zones like those found in the state of Rajasthan. The implications of the research findings are that the combination of a traditional hydrological model and the use of an advanced artificial intelligence can significantly increase the effectiveness and credibility of the water resources evaluation. The shortcomings of physically based watershed models can be offset using the capabilities of the AI algorithms through hybrid modelling frameworks. These combined methods come in especially handy when it comes to assessing basin-wide hydrological changes to changing climatic conditions and growing anthropogenic stressors. Introduction of these techniques can be relevant to enhance watershed management, efficient functionality of the reservoirs, and enhanced division of limited water resources to various sectors in Rajasthan. Further study needs to be based on the design of unified modelling systems, which would unite models of hydrological simulation with the methodologies of artificial intelligence and machine learning. The consideration of long-term hydro-meteorological records, high-resolution data on remote sensing, and climate change simulations can greatly increase the accuracy and usefulness of the water resources models in the area. More research studies should also focus on incorporating surface water and groundwater systems in order to reflect more on the interdependency between hydrological processes, which govern the availability of the water in Rajasthan. The hybrid modelling approaches to the development of decision-support systems will avail more reliable sustainable water resources planning, drought reduction, and climate-resilient water management strategies of the state to policymakers and water managers.

VIII. AUTHOR'S CONTRIBUTION

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