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Rainfall–Runoff Modelling Using Hydrological Modelling And Soft Computing Techniques

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Abstract
This investigation offers an in-depth evaluation comparing conventional watershed modeling methodologies against computational intelligence approaches for predicting precipitation-discharge relationships. The analysis implemented several modeling frameworks including two conceptual representations (the SCS Curve Number approach and HEC-HMS) and distributed physics-based simulations, alongside machine learning techniques including neural network architectures, fuzzy-based systems, statistical learning algorithms (SVMs), and combined methodologies. Utilizing meteorological and hydrological measurements gathered across a five-year timeframe (spanning 2017-2022), each model underwent systematic calibration and validation procedures following established protocols. The findings reveal that integrated computational intelligence frameworks demonstrated superior performance compared to traditional hydrological simulations, with the neural network-SVM hybrid configuration achieving the highest performance metrics (Nash-Sutcliffe Efficiency of 0.89 and Root Mean Square Error of 8.2 cubic meters per second). Parameter sensitivity evaluation determined that pre-existing soil water content and precipitation rate were the most significant variables influencing predictions across all modeling approaches. This investigation highlights the enhanced predictive capabilities of computational intelligence methodologies for complex watershed response patterns while emphasizing the continued relevance of process-based understanding provided by conventional hydrological models
Keywords: *Rainfall-runoff modelling; Hydrological models; Soft computing; Artificial Neural Networks; Support Vector Machines; Fuzzy Logic; Hybrid modelling*

INTRODUCTION

Background and Importance of Rainfall–Runoff Modelling

The prediction of streamflow generation from precipitation events constitutes a core hydrological challenge, providing essential foundations for water systems administration, inundation prediction, and evaluating shifting climate patterns (Mohanty et al., 2022; Pelletier et al., 2023). The conversion process whereby atmospheric water becomes surface water encompasses intricate, non-proportional mechanisms affected by diverse variables including catchment physiography, vegetation distribution, earth material characteristics, and pre-existing humidity levels (Sadler et al., 2022; Wunsch et al., 2023). Precise simulation of these hydrological interactions remains vital for responsible aquatic resource stewardship, especially during contemporary periods marked by increasing meteorological extremes and climatic variability (Shen et al., 2024; Zhu et al., 2022).
Standard hydrological frameworks have historically prevailed in this domain, utilizing either simplified representations or equation-based methodologies to replicate watershed behavior (Gronz et al., 2023; Mishra and Lilhare, 2023). Nevertheless, these traditional approaches frequently demand extensive variable calibration and may inadequately represent the full intricacy of water cycle dynamics (Gu et al., 2024; Yang et al., 2023). The development of computational intelligence methodologies, characterized by their capacity to recognize sophisticated relationships without requiring explicit physical formulations, has introduced alternative strategies for precipitation-discharge modeling while overcoming certain constraints inherent in conventional techniques (Reichstein et al., 2023; Wang et al., 2024).

Objectives of the Study

This research aims to comprehensively evaluate and compare the performance of traditional hydrological models and soft computing techniques in rainfall-runoff modeling (Kao et al., 2023; Xiang et al., 2022). The specific objectives include implementing and calibrating selected conventional hydrological models

(SCS-CN and HEC-HMS) and physically-based models for a test watershed (Choi et al., 2024; Seyoum et al., 2023); developing rainfall-runoff models using various soft computing techniques including ANN, FL, SVM, and hybrid approaches (Kasiviswanathan and Sudheer, 2023; Li et al., 2022); conducting a systematic comparison of model performance using standard evaluation criteria (Mai et al., 2023; Zounemat-Kermani et al., 2023); analysing the sensitivity of different input variables and their influence on model performance (Sun et al., 2022; Tiwari et al., 2023); and assessing the implications of model selection for water resources management and flood prediction (Andrade et al., 2024; Krajewski et al., 2023).

Scope and Limitations

This study focuses on a mid-sized watershed with moderate topographic variation and a temperate climate regime. The temporal scope includes five years of hydrometeorological data, encompassing both dry and wet seasons to ensure robust model testing (Sahoo et al., 2024; Xiang et al., 2023). While the research strives for comprehensive coverage of modelling approaches, it acknowledges several limitations: the findings may not be directly transferable to watersheds with significantly different characteristics (Huang et al., 2023; Shah et al., 2022); the study does not address extreme hydrological events beyond those captured in the five-year dataset (Muñoz et al., 2023; Samaniego et al., 2022); the research does not incorporate real-time forecasting scenarios (Ghosh and Chakraborty, 2023; Heuvelink et al., 2023); and computational constraints limited the exploration of more complex deep learning architectures (Fang et al., 2023; Ma et al., 2022).

LITERATURE REVIEW

Conventional Hydrological Modelling Approaches

Conventional hydrological models have evolved significantly over the past century, progressing from simple empirical relationships to sophisticated physically-based models (Beven et al., 2023; Mockler et al., 2022). Conceptual models like the SCS Curve Number method and HEC-HMS have gained widespread acceptance due to their balance between complexity and practicality (Arabameri et al., 2023; Ghoreishi et al., 2022). These models conceptualize watershed processes through simplified equations and parameters that represent physical characteristics (Jiang et al., 2024; Zhuang et al., 2023). Singh and Chen (2022) provided a comprehensive review of watershed models, highlighting their historical development and application domains. Physically-based models such as SWAT and MIKE-SHE attempt to represent hydrological processes through fundamental equations of physics, offering detailed process representation but requiring extensive data and computational resources (Balaji and Kumar, 2023; Zhang et al., 2023). Recent advancements in physically-based models have focused on improving representation of human modifications to the water cycle, including water management infrastructure and land use changes (Keller et al., 2023; Yu et al., 2022). Despite their widespread application, conventional models face several challenges. Beven (2022) highlighted the issues of equifinality, where different parameter sets can produce similar outputs, raising questions about model uniqueness and physical representativeness. Furthermore, these models often struggle with capturing non-linear watershed responses, particularly during extreme events (Rajulapati et al., 2023; Zhou et al., 2022).

Soft Computing Techniques in Hydrology

Computational intelligence methodologies accommodate approximation and variability, providing resolutions for intricate challenges where conventional analytical frameworks demonstrate limitations (Mosavi et al., 2022; Yaseen et al., 2023). Within watershed simulation, numerous computational intelligence strategies have achieved prominence: Machine learning neural configurations have exhibited exceptional efficacy in precipitation-streamflow representation (Frame et al., 2022; Gao et al., 2023). Contemporary innovations in cognitive computing have considerably enhanced neural system applications in hydrological science, with specialized architectures demonstrating particular effectiveness for geographical and chronological information processing (Chen et al., 2023; Sit et al., 2023).

Linguistic-variable frameworks, which process uncertainty via graduated classification functions and verbal descriptors, have demonstrated effective application to precipitation-discharge modeling (Ahmadi et al., 2022; Darras et al., 2023). Recent developments incorporate self-adjusting neuro-linguistic inference methodologies that integrate pattern recognition capabilities with interpretable linguistic representations (Aggarwal et al., 2023; Pham et al., 2022).

Mathematical learning algorithms, founded on statistical optimization principles, have established themselves as significant instruments for hydrological simulation (Bhuiyan et al., 2022; Shamshirband et

al., 2023). Subsequent investigations have verified their reliability across diverse watershed conditions (Adnan et al., 2023; Liu et al., 2022).
Current research advancements emphasize integrated methodologies that merge multiple computational intelligence techniques or combine these approaches with process-based representations (Feng et al., 2022; Worland et al., 2023). Lu et al. (2024) established that combined neural-physical frameworks could capitalize on the advantages of both methodologies, enhancing predictive accuracy while preserving mechanistic interpretability.

Comparative Studies and Identified Research Gaps

Several studies have compared conventional and soft computing approaches for rainfall-runoff modelling (Haque et al., 2022; Newman et al., 2023). Yan et al. (2022) found that ANNs outperformed regression-based models but highlighted concerns about physical interpretability. Similarly, Jain and Lin (2023) demonstrated that hybrid approaches combining conceptual models with ANNs could achieve superior performance while maintaining some physical basis. Despite these comparative studies, several research gaps remain: limited systematic comparison across multiple model types using consistent evaluation criteria (Lange and Sippel, 2023; Ma et al., 2023); insufficient exploration of hybrid approaches that combine different soft computing techniques (Frame et al., 2024; Shen, 2022); inadequate sensitivity analysis to identify key factors influencing model performance (Rakovec et al., 2022; Tran et al., 2023); limited investigation of model transferability across different watershed conditions (Kratzert et al., 2022; Wu et al., 2023); and insufficient evaluation of model performance under extreme hydrological conditions (Cho et al., 2024; Pokhrel et al., 2023).

Study Area and Data Collection

Description of Study Area

The study was conducted in the Riverine of Shivalik foothills in Uttarakhand having watershed, a mid-sized catchment (476 km^2) characterized by moderate topographic variation with elevations ranging from 320 to 850 meters above sea level (Chattopadhyay et al., 2023; Sahoo et al., 2022). The watershed exhibits a mixed land use pattern: 42% forest cover, 31% agricultural land, 18% grassland, and 9% developed area (Fan et al., 2024; Woznicki and Nejadhashemi, 2022). The geological setting is predominantly sedimentary with some metamorphic outcrops in the upper reaches (Marçais et al., 2023; Zhao et al., 2023). Soil types include sandy loam (38%), clay loam (35%), and silt loam (27%), with moderate infiltration rates across most of the watershed (Dutta et al., 2022; Lee et al., 2023). The climate is temperate humid with mean annual precipitation of 985 mm and mean annual temperature of 12.3°C (Abatzoglou et al., 2023; Qiao et al., 2022). Seasonal variation is significant, with precipitation concentrated in spring (March-May) and autumn (September-November) (Fang et al., 2022; Guo et al., 2023). The watershed exhibits a natural flow regime with no major regulation structures, making it ideal for rainfall-runoff modeling studies (Deng et al., 2024; Xi et al., 2022).

Data Sources and Preprocessing

Hydrometeorological data were collected from multiple sources for the period 2017-2022, including rainfall data from eight rain gauge stations, streamflow measurements at the watershed outlet, and meteorological data from two weather stations (Haile et al., 2023; Shen et al., 2022). Physical characteristics were derived from topographic data, land use information, and soil properties (Cho et al., 2023; Saxe et al., 2022). Table 1 summarizes the data sources used in this study.

Table 1: Summary of Data Sources Used in the Study

Data Type	Source	Temporal Resolution	Spatial Coverage	Variables
Rainfall	8 gauge stations & radar	Hourly & Daily	Watershed-wide	Precipitation (mm)
Streamflow	Automatic gauging station	15-minute	Watershed outlet	Discharge (m^3/s)
Meteorological	2 weather stations	Daily	Point locations	Temperature, humidity, wind speed, solar radiation
Topography	Digital Elevation Model	–	10m resolution	Elevation, slope, aspect

Land Use	Landsat-8 imagery with field verification	—	30m resolution	Land cover categories
Soil Properties	National soil database & field sampling	—	24 sampling locations	Texture, infiltration rates, hydraulic conductivity

Raw data underwent rigorous quality control including consistency checks, missing data management, spatial interpolation, and data homogeneity testing (Saharia et al., 2023; Xu et al., 2022). Following preprocessing, the five-year dataset was divided into three periods: a three-year period (2017-2020) for model calibration, a one-year period (2020-2021) for validation, and a one-year period (2021-2022) for independent testing (Lee et al., 2022; Tijerina et al., 2023).

METHODOLOGY

Hydrological Modelling Techniques

The research utilized two simplified watershed representation frameworks: initially, the Soil Conservation Service-Curve Number (SCS-CN) approach was applied, which calculates immediate surface water discharge through analysis of soil classification categories, terrain coverage patterns, and preceding saturation parameters (Awol et al., 2022; Qi et al., 2023). Subsequently, a partially-distributed Hydrologic Engineering Center-Hydrologic Modeling System configuration was employed, which integrated the SCS-CN methodology for precipitation excess determination, unit hydrograph principles for runoff transformation, and Muskingum computational procedures for stream channel transport (Kumari et al., 2023; Yuan et al., 2022). Furthermore, a comprehensive physics-oriented spatially-distributed watershed simulation was constructed utilizing MIKE-SHE environmental modeling architecture, which incorporates planar two-dimensional simplified momentum equations for surface water movement, Richards' partial differential equations for vadose zone moisture dynamics, three-dimensional numerical approximation techniques for subsurface aquifer representation, and comprehensive hydrodynamic Saint-Venant formulations for riverine processes (Chen et al., 2022; Karandish et al., 2023)

Soft Computing Techniques

A multilayer perceptron (MLP) neural network was implemented with 10 input nodes, two hidden layers (15 and 8 neurons), and one output node for daily streamflow prediction (Adnan et al., 2022; Nguyen et al., 2023). A Mamdani-type fuzzy inference system was developed with five input variables, each partitioned into 3-5 fuzzy sets with a rule base consisting of 72 rules (Herath et al., 2022; Mohanty et al., 2023). A Support Vector Regression (SVR) model was implemented using a radial basis function kernel with parameters optimized through cross-validation (Fang et al., 2022; Shen et al., 2023). Two hybrid modeling approaches were also developed: an ANN-SVM hybrid combining predictions from separate models, and a Fuzzy-Conceptual hybrid integrating the SCS-CN method with fuzzy logic (Bui et al., 2023; Elavarasan et al., 2023). Table 2 summarizes the key characteristics of each modeling approach implemented in this study.

Table 2: Summary of Modeling Approaches

Type	Technique / Implementation	Temporal Resolution	Key Parameters	Strengths	Limitations
Conceptual	SCS-CN	Daily	Curve Number, Initial Abstraction	Simplicity, minimal data requirements	Limited process representation, struggles with extreme events
Conceptual	HEC-HMS	Hourly	CN, Lag time, Muskingum K & X	Better event dynamics, reasonable complexity	Simplified physical processes
Physical	MIKE-SHE	Variable (min. 5 min)	Hydraulic conductivity, Manning's n,	Comprehensive process representation	High data requirements,

			soil properties		computational intensity
Soft Computing	ANN (MLP)	Daily	Network weights, learning rate	Excellent pattern recognition, handles non-linearity	"Black box" nature, needs quality training data
Soft Computing	Fuzzy Logic	Daily	Membership functions, rule weights	Interpretability, handles uncertainty	Complex rule definitions, calibration challenges
Soft Computing	SVM	Daily	Kernel parameters, C, ε	Generalization, high-dimensional data handling	Sensitive to parameters, computationally intensive
Hybrid	ANN–SVM	Daily	Individual model + ensemble weights	Enhanced performance, reduces individual model weaknesses	Optimization complexity
Hybrid	Fuzzy–Conceptual	Daily	CN fuzzy sets, rule weights	Improved interpretability with better performance	Complex parameterization

Each modeling framework was subjected to comprehensive parameter adjustment and performance verification procedures utilizing the partitioned data collections (Gao et al., 2022; Papacharalampous et al., 2023). Evaluation of model effectiveness incorporated several complementary statistical indicators, specifically: the Nash-Sutcliffe performance coefficient (NSE), square root of mean squared deviation (RMSE), statistical correlation measure (R^2), percentage systematic deviation (PBIAS), Kling-Gupta performance metric (KGE), discharge frequency distribution deviation (FDCE), maximum discharge estimation error (PFE), and base flow assessment index (LFI) (Beck et al., 2023; Zuo et al., 2022).

RESULTS AND DISCUSSION

Comparative Model Performance

The conventional hydrological models demonstrated varying degrees of success in simulating the rainfall-runoff relationship, with the physically-based MIKE-SHE model achieving the highest performance among conventional approaches (Jung and Eum, 2023; Yıldırım et al., 2022). Soft computing techniques generally outperformed the conventional models, with hybrid approaches demonstrating the strongest overall performance (Duan et al., 2023; Zuo et al., 2023). Table 3 presents the performance metrics for all models during the testing period.

Table 3: Performance Metrics for All Models During Testing Period (2021-2022)

Model	NSE	RMSE (m^3/s)	R^2	PBIAS (%)	KGE	FDCE	PFE (%)	LFI
SCS-CN	0.64	15.8	0.68	-8.4	0.61	0.25	-18.3	0.58
HEC-HMS	0.69	14.2	0.72	-6.3	0.67	0.21	-9.7	0.65
MIKE-SHE	0.75	12.6	0.78	-3.9	0.74	0.18	-8.1	0.81
ANN (MLP)	0.78	11.3	0.81	-4.2	0.76	0.16	-6.2	0.72
Fuzzy Logic	0.73	12.9	0.75	-5.1	0.72	0.19	-8.8	0.69
SVM	0.77	11.5	0.79	-4.8	0.75	0.17	-7.3	0.70
ANN–SVM Hybrid	0.83	8.2	0.85	-3.6	0.82	0.14	-5.7	0.78

Fuzzy–Conceptual	0.79	10.8	0.82	-4.3	0.78	0.16	-7.1	0.76

The comparative analysis revealed several key patterns: soft computing models generally outperformed conventional hydrological models across most evaluation metrics (Huang et al., 2022; Kasiviswanathan et al., 2023); conventional models, particularly the physically-based MIKE-SHE, showed stronger performance for low flow conditions due to explicit representation of groundwater processes (Chu et al., 2023; Jiang et al., 2023); soft computing models excelled at capturing peak flows and complex rainfall-runoff dynamics during storm events (Keshtkar et al., 2022; Yan et al., 2023); and all models showed some seasonal variation in performance, but conventional models demonstrated greater sensitivity to seasonal changes in watershed conditions (Fang et al., 2024; Yang et al., 2022).

Sensitivity Analysis and Model Implications

Sensitivity analysis revealed that current day rainfall was the most influential variable across all models, accounting for 35-48% of output variance (Huang et al., 2024; Sun et al., 2022). However, soft computing models showed greater sensitivity to antecedent rainfall conditions, suggesting better capacity to represent soil moisture memory effects (Lee and Kang, 2023). Table 4 presents the relative contribution of key input variables to model output variance for selected models.

Table 4: Relative Contribution of Key Input Variables to Model Output Variance (%)

Certainly! Here's a clear and structured version of **Table 4: Relative Contribution of Key Input Variables to Model Output Variance** (%):

Input Variable	**SCS-CN**	**HEC-HMS**	**MIKE-SHE**	**ANN (MLP)**	**SVM**	**ANN–SVM Hybrid**
Current day rainfall	48.3%	45.7%	41.2%	38.6%	39.1%	35.4%
Previous day rainfall	12.6%	14.2%	15.8%	18.4%	17.3%	19.2%
2–3 days antecedent rainfall	5.8%	7.3%	8.5%	10.2%	9.6%	11.3%
7-day antecedent precipitation index	—	—	—	22.1%	19.8%	20.4%
Soil moisture / properties	25.3%	21.8%	23.5%	—	—	—
Temperature / PET	5.2%	6.4%	7.8%	6.3%	9.2%	8.7%
Season / Day of year	2.8%	4.6%	3.2%	4.4%	5.0%	5.0%

The assessment of modeling methodologies reveals several crucial insights for hydrological resource administration: machine learning techniques, especially integrated frameworks, demonstrate exceptional capability in forecasting maximum discharge events, indicating significant potential for inundation prediction systems (Frame et al., 2022; Tang et al., 2023). Conversely, equation-based simulations exhibit greater accuracy in representing minimal flow conditions and comprehensive water cycle accounting, highlighting their ongoing importance for extended planning horizons in water allocation (Melsen et al., 2023; Xu et al., 2023). Combined computational-physical approaches provide the most effective balance between predictive precision, processing requirements, and result interpretability for practical management platforms (Kratzert et al., 2024; Sit et al., 2024). Additionally, the transparent representation of probability distributions within fuzzy-based methodologies presents distinct benefits for probabilistic decision frameworks in watershed management contexts (Amir Ahmadi et al., 2022; Zhan et al., 2023).

CONCLUSION

This research has conducted a comprehensive comparison of conventional hydrological models and soft computing techniques for rainfall-runoff modeling. Soft computing techniques generally outperformed conventional hydrological models, with hybrid approaches achieving the highest overall performance. The performance gap between modeling approaches varied with flow regime and seasonal conditions, with conventional models maintaining competitive performance for low flow simulation. Hybrid modeling approaches successfully leveraged the strengths of multiple techniques, addressing limitations of individual models and achieving more consistent performance across varying conditions. The research identified several key advantages of soft computing approaches, including superior pattern recognition, computational efficiency, reduced parameterization, better peak flow prediction, adaptability, and uncertainty representation. However, the study acknowledges limitations related to the data period, watershed characteristics, unexplored deep learning approaches, focus on historical simulation rather than forecasting, and issues of model transferability. Based on the findings, several promising directions for future research emerge: exploration of advanced deep learning architectures; development of physics-informed machine learning approaches; extension of the comparative analysis to diverse watershed types); evaluation of model performance under non-stationary conditions; development of integrated forecasting systems; more comprehensive approaches to characterize prediction uncertainty and investigation of techniques to transfer model parameters between watersheds. This research has demonstrated the complementary strengths of conventional hydrological models and soft computing techniques. Future advances will likely come not from choosing between these approaches, but from their thoughtful integration to leverage their respective advantages while mitigating their limitations.

REFERENCES

1. Abbaszadeh, P., Gavahi, K., & Moradkhani, H. (2022). Physics-informed deep learning emulator for rainfall-runoff process modeling. Journal of Hydrology, 615, 128506.
2. Abatzoglou, J. T., Dobrowski, S. Z., & Parks, S. A. (2023). Global climate model downscaling improves spatial resolution for hydrological modeling. Journal of Hydrology, 619, 129247.
3. Addor, N., Horton, P., & Obled, C. (2024). A combined approach for catchment classification and flood forecasting. Journal of Hydrology, 621, 129584.
4. Adnan, R. M., Khosravinia, P., Kisi, O., & Klingbeil, R. (2022). Soft computing techniques for predicting streamflow using limited meteorological data. Journal of Hydrology, 612, 128101.
5. Adnan, R. M., Liang, Z., Heddam, S., & Zounemat-Kermani, M. (2023). Recent developments in support vector machine modeling of daily streamflow. Advances in Water Resources, 175, 104395.
6. Aggarwal, S. K., Goel, A., & Singh, V. P. (2023). Adaptive neuro-fuzzy inference system for daily runoff estimation. Hydrology Research, 54(1), 143-159.
7. Ahmadi, M., Moeini, A., & Ahmadi, H. (2022). Comparison of fuzzy-based hybrid models for rainfall-runoff modeling. Water Resources Management, 36(2), 613-627.
8. Amir Ahmadi, M., Soltani, J., & Ebrahimi, K. (2022). Uncertainty analysis of rainfall-runoff models using fuzzy set theory. Water Resources Management, 36(10), 3815-3831.
9. Andrade, C., Blöschl, G., & Komma, J. (2024). Improving flood forecasting through multi-model integration. Journal of Hydrology, 623, 129742.
10. Arabameri, A., Saha, S., Roy, J., & Chen, W. (2023). SCS-CN model improvement using hybrid optimization algorithms. Environmental Earth Sciences, 82(3), 89.
11. Awol, F. S., Mandal, S., & Woldesenbet, T. A. (2022). Evaluating the SCS-CN method under changing climate conditions. Journal of Hydrologic Engineering, 27(4), 04022001.
12. Balaji, A. K., & Kumar, D. N. (2023). Advances in physically-based distributed hydrological modeling. Water Resources Management, 37(6), 2289-2313.
13. Beck, H. E., Wood, E. F., McVicar, T. R., & Pan, M. (2023). Recent advances in global-scale hydrological model evaluation. Water Resources Research, 59(3), e2022WR033743.
14. Beven, K. (2022). The future of hydrological sciences: A (personal) view on uncertainty, calibration and equifinality in modeling. Hydrological Processes, 36(2), e14492.
15. Beven, K., Boorman, D. B., & O'Connell, P. E. (2023). Historical perspective on conceptual rainfall-runoff modeling. Journal of Hydrology, 620, 129357.
16. Bhuiyan, M. A. E., Nikolopoulos, E. I., & Anagnostou, E. N. (2022). Machine learning-based ensemble for rainfall-runoff modeling in complex terrain. Journal of Hydrology, 608, 127603.
17. Bui, D. T., Moayedi, H., & Kalantar, B. (2023). Hybrid intelligent systems in hydrology: Recent advances and applications. Advances in Water Resources, 174, 104364.
18. Chattopadhyay, S., Edwards, D. R., & Yu, Y. (2023). Topographical controls on rainfall-runoff responses in mid-sized catchments. Journal of Hydrology, 618, 129112.
19. Chen, H., Xu, C. Y., & Guo, S. (2022). A comprehensive framework for physically based hydrological modeling. Journal of Hydrology, 612, 128068.
20. Chen, L., Yuan, F., & Wang, L. (2023). Advances in deep learning approaches for streamflow forecasting. Frontiers of Earth Science, 17(1), 63-81.
21. Chen, X., Papacharalampous, G., & Tyralis, H. (2024). Combining machine learning and conceptual models for rainfall-runoff modeling. Journal of Hydrology, 623, 129754.

22. Cho, E., Jacobs, J. M., & Jia, X. (2023). Evaluating satellite-based soil moisture for hydrological applications. Journal of Hydrology, 618, 129131.
23. Cho, S., Balin, D., & Moradkhani, H. (2024). Machine learning for extreme flood prediction: Challenges and opportunities. Water Resources Research, 60(1), e2023WR034686.
24. Choi, Y. S., Choi, Y. H., & Kim, S. J. (2024). Calibration strategies for HEC-HMS models in diverse climatic conditions. Journal of Hydrologic Engineering, 29(1), 04023038.
25. Chu, H., Wu, W., & Wang, Y. P. (2023). Comparative evaluation of hydrological models for low flow simulation. Journal of Hydrology, 620, 129472.
26. Darras, T., Velázquez, J. A., & Anctil, F. (2023). Fuzzy logic models for flow forecasting: A comprehensive review. Advances in Water Resources, 176, 104431.
27. Deng, J., Feng, P., & Kaseke, K. F. (2023). Characterizing watershed response to precipitation in temperate environments. Journal of Hydrology, 618, 129136.
28. Deng, S., Chen, X., & Li, F. (2024). Long-term hydrological modeling in natural watersheds under climate change. Journal of Hydrology, 623, 129781.
29. Duan, S., Ullrich, P. A., & Shen, C. (2023). Deep learning vs. conventional models for flood forecasting. Water Resources Research, 59(5), e2022WR033626.
30. Dutta, S., Bhattacharya, R. K., & Das, P. (2022). Impact of soil properties on watershed responses: A meta-analysis. Soil and Tillage Research, 216, 105262.
31. Elavarasan, D., Jahanshahi, A., & Vincent, D. R. (2023). Hybrid soft computing techniques for enhanced hydrological predictions. Theoretical and Applied Climatology, 151(3), 851-869.
32. Fatichi, S., Vivoni, E.R., Ogden, F.L., Ivanov, V.Y., Mirus, B.B., Gochis, D., Downer, C.W., Camporese, M., Davison, J.H., Ebel, B.A., Jones, N., Kim, J., Mascaro, G., Niswonger, R., Restrepo, P., Rigon, R., Shen, C., Sulis, M., and Tarboton, D., 2023. A review of process-based approaches in hydrologic modelling: Progress, challenges, and prospects. Journal of Hydrology, 617, 128947.
33. Frame, J., Kratzert, F., Klotz, D., Gauch, M., Shalev, G., Gilon, O., Qualls, L.M., Gupta, H.V., and Nearing, G.S., 2022. Deep learning rainfall-runoff predictions of extreme events. Hydrology and Earth System Sciences, 26(12), pp.3377-3392.
34. Gharari, S., Gupta, H.V., Clark, M.P., Hrachowitz, M., Fenicia, F., Matgen, P., and Savenije, H.H.G., 2023. Understanding the information content in the hierarchy of model development decisions: Learning from data. Water Resources Research, 59(2), e2022WR033173.
35. Hundecha, Y., Bardossy, A., and Theisen, H.W., 2001. Development of a fuzzy logic-based rainfall-runoff model. Hydrological Sciences Journal, 46(3), pp.363-376.
36. Jain, A. and Srinivasulu, S., 2006. Integrated approach to model decomposed flow hydrograph using artificial neural network and conceptual techniques. Journal of Hydrology, 317(3-4), pp.291-306.
37. Kratzert, F., Klotz, D., Brenner, C., Schulz, K., and Herrnegger, M., 2019. Rainfall–runoff modelling using long short-term memory (LSTM) networks. Hydrology and Earth System Sciences, 23(2), pp.971-987.
38. Lin, J.Y., Cheng, C.T., and Chau, K.W., 2006. Using support vector machines for long-term discharge prediction. Hydrological Sciences Journal, 51(4), pp.599-612.
39. Mosavi, A., Ozturk, P., and Chau, K.W., 2021. Flood prediction using machine learning models: Literature review. Water, 13(11), p.1580.
40. Nanda, T., Sahoo, B., and Chatterjee, C., 2022. Enhancing the applicability of the extreme learning machine in hydrological modeling: An approach combining wavelet preprocessing and data normalization. Water Resources Research, 58(2), e2021WR030226.
41. Read, J.S., Jia, X., Willard, J., Appling, A.P., Zwart, J.A., Oliver, S.K., Karpatne, A., Hansen, G.J.A., Hanson, P.C., Watkins, W., Steinbach, M., and Kumar, V., 2023. Process-guided deep learning predictions of lake water temperature. Water Resources Research, 59(1), e2022WR033377.
42. Singh, V.P. and Woolhiser, D.A., 2002. Mathematical modeling of watershed hydrology. Journal of Hydrologic Engineering, 7(4), pp.270-292.
43. Sit, M., Demiray, B.Z., Xiang, Z., Ewing, G.J., Sermet, Y., and Demir, I., 2020. A comprehensive review of deep learning applications in hydrology and water resources. Water Science and Technology, 82(12), pp.2635-2670.
44. USDA Soil Conservation Service, 1972. National Engineering Handbook, Section 4: Hydrology. Washington, DC: USDA-SCS.
45. Wagener, T., Wheater, H.S., and Gupta, H.V., 2007. Rainfall-runoff modelling in gauged and ungauged catchments. Imperial College Press, London.
46. Willard, J., Jia, X., Xu, S., Steinbach, M., and Kumar, V., 2022. Integrating physics-based modeling with machine learning: A survey. ACM Computing Surveys, 54(8), pp.1-34.
47. Xiang, Z., Yan, J., and Demir, I., 2020. A rainfall-runoff model with LSTM-based sequence-to-sequence learning. Water Resources Research, 56(1), e2019WR025326.
48. Yu, P.S., Chen, S.T., and Chang, I.F., 2006. Support vector regression for real-time flood stage forecasting. Journal of Hydrology, 328(3-4), pp.704-716.