

# RAINFALL-RUNOFF PREDICTION USING DATA-DRIVEN MODELING TECHNIQUES

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## ABSTRACT

*Rainfall-runoff (RR) modeling forms the analytical backbone of sustainable water resources management, underpinning flood forecasting, reservoir operation, drought planning, and watershed-scale decision making. This review and meta-analysis synthesizes findings from more than ninety peer-reviewed studies published between 2000 and 2024, spanning empirical, conceptual, physically-based distributed, and data-driven artificial-intelligence approaches to RR modeling. The paper traces the historical evolution of modeling paradigms, from the unit hydrograph and Soil Conservation Service Curve Number methods to contemporary machine-learning architectures such as artificial neural networks, support vector machines, and long short-term memory networks, and examines how each paradigm addresses the persistent challenges of parameter uncertainty, spatial heterogeneity, and non-stationarity induced by climate and land-use change. A structured methodology, informed by PRISMA-style screening, was used to identify, filter, and synthesize the literature quantitatively and qualitatively. The meta-analysis reveals that hybrid physically-informed machine-learning models consistently outperform purely empirical or purely data-driven counterparts in terms of Nash-Sutcliffe efficiency, particularly in data-scarce and ungauged basins. The critical analysis further highlights recurring limitations across the literature, including overreliance on single-basin validation, inadequate uncertainty quantification, and limited transferability of trained models across climatic regimes. The discussion situates these findings within the broader goals of sustainable water governance, arguing for greater standardization of benchmarking datasets and increased integration of remote-sensing inputs. The review concludes that future RR modeling research must prioritize explainability, transfer*

*learning, and coupling with decision-support frameworks to translate modeling advances into actionable water resources management outcomes.*

**Keywords:** *Rainfall-runoff modeling<sup>1</sup>; Sustainable water resources management<sup>2</sup>; Hydrological models<sup>3</sup>; Machine learning in hydrology<sup>4</sup>; Watershed modeling<sup>5</sup>; Model uncertainty<sup>6</sup>; Meta-analysis<sup>7</sup>*

## 1. INTRODUCTION

### 1.1 Background and Significance

Water resources management has become increasingly complex under the combined pressures of population growth, rapid urbanization, and climate variability, making accurate prediction of catchment response to rainfall a foundational requirement for planning and policy[1]. Rainfall-runoff modeling translates precipitation inputs into streamflow outputs through mathematical representations of hydrological processes such as interception, infiltration, evapotranspiration, and baseflow recession[2]. Since the earliest rational-method formulations of the nineteenth century, the field has progressed through successive generations of models that trade off simplicity, data requirements, and physical realism. The growing availability of remote-sensing precipitation products, digital elevation models, and long-term streamflow records has expanded the scope of feasible modeling approaches, while simultaneously raising expectations regarding predictive accuracy and generalizability across diverse hydroclimatic settings[3].

### 1.2 Motivation for a Review and Meta-Analysis

Despite decades of methodological advancement, the rainfall-runoff modeling literature remains fragmented across disciplinary silos: civil and environmental engineering, statistical hydrology, and computer science each contribute distinct modeling philosophies that are rarely compared on common ground[4]. Narrative reviews have periodically summarized specific model families, but few studies have undertaken a systematic, quantitative synthesis that spans empirical, conceptual, physically-based, and machine-learning paradigms simultaneously. This gap motivates the present review, which aims to consolidate reported performance metrics, identify methodological trends over time, and critically evaluate the strengths and limitations of past work in a manner that is directly useful to researchers and practitioners engaged in sustainable water resources planning[5].

### 1.3 Objectives and Scope of the Review

This paper pursues three interconnected objectives. First, it provides a structured survey of the major categories of rainfall-runoff models reported in the literature over the past two decades, describing their theoretical basis and typical application contexts[6]. Second, it performs a meta-analytic synthesis of reported performance indicators,

principally the Nash-Sutcliffe efficiency and coefficient of determination, to compare model categories on a common quantitative basis[7]. Third, it critically analyzes recurring methodological weaknesses in past studies, including validation practices, uncertainty treatment, and transferability, and discusses their implications for sustainable water governance[8]. The scope is deliberately broad, encompassing studies from humid, arid, and mixed hydroclimatic regions, in order to capture the diversity of modeling practice while remaining focused specifically on surface rainfall-runoff transformation rather than the broader hydrological cycle[9].

## 2. SURVEY OF PAST WORK

The earliest attempts at rainfall-runoff modeling were empirical in nature, relying on simple algebraic relationships between rainfall intensity, catchment characteristics, and peak discharge. The Rational Method, still taught as an introductory design tool, estimates peak runoff as a product of a runoff coefficient, rainfall intensity, and catchment area, and remains widely used for small urban catchments despite well-documented limitations in capturing temporal dynamics[10]. The Soil Conservation Service Curve Number (SCS-CN) method, developed in the mid-twentieth century, extended empirical modeling by relating cumulative runoff to cumulative rainfall through an empirically derived curve number that reflects land use, soil type, and antecedent moisture condition; numerous studies reviewed here report its continued application and periodic recalibration across diverse geographic settings, alongside critiques regarding its insensitivity to storm duration and its assumption of a fixed initial abstraction ratio[11].

Conceptual, or lumped-parameter, models emerged as a response to the limitations of purely empirical formulations, representing catchment processes through interconnected storage reservoirs governed by simplified physical relationships[12]. The Stanford Watershed Model, HBV, TANK, and Xinanjiang models are among the most extensively studied conceptual frameworks in the surveyed literature, each employing a small number of calibratable parameters to represent soil moisture accounting, interflow, and baseflow recession[13]. These models strike a balance between computational efficiency and physical interpretability, and a substantial body of past work demonstrates their successful application to flood forecasting and long-term water balance studies, particularly in regions with moderate data availability. However, the survey reveals persistent concerns regarding parameter equifinality, whereby multiple parameter sets yield statistically indistinguishable performance, complicating the physical interpretation of calibrated values[14].

Physically-based distributed models represent a further step toward process realism by discretizing catchments into grid cells or sub-basins and solving governing equations for surface and subsurface flow explicitly. Models such as SWAT (Soil and Water Assessment Tool), MIKE SHE, TOPMODEL, and HEC-HMS feature prominently across the reviewed literature, particularly in studies addressing land-use change impacts, best management practice evaluation, and climate change scenario analysis[15]. These models offer the advantage of spatially distributed outputs and explicit representation of physical processes, enabling scenario-based

experimentation that lumped models cannot easily support. Nonetheless, the survey identifies recurring challenges related to extensive data requirements, high computational cost, and substantial calibration effort, which have historically limited their application in data-scarce basins common throughout much of the developing world[16].

The past decade has witnessed a marked shift toward data-driven and machine-learning approaches, reflecting both the increasing availability of hydrometeorological data and advances in computational methods. Artificial neural networks (ANNs) were among the earliest machine-learning techniques applied to rainfall-runoff prediction, with numerous studies in the 2000s and 2010s reporting competitive or superior performance relative to conceptual models, particularly for short-term flow forecasting[17]. Support vector machines and random forest regressors subsequently gained traction for their robustness to overfitting in moderate-sized datasets. More recently, deep-learning architectures, particularly long short-term memory (LSTM) networks, have demonstrated strong capability in capturing the temporal dependencies inherent in rainfall-runoff processes, with several large-sample studies reporting performance that rivals or exceeds physically-based models across hundreds of catchments simultaneously[18]. The survey also identifies an emerging body of work on hybrid and physics-informed machine-learning models, which embed physical constraints or conceptual model structures within a machine-learning framework, aiming to combine the interpretability of process-based models with the predictive flexibility of data-driven methods.

Beyond model structure, the surveyed literature reflects growing attention to input data quality and resolution, with numerous studies examining the sensitivity of rainfall-runoff predictions to rain-gauge density, satellite-based precipitation products, and radar-derived rainfall estimates. Comparative studies consistently find that model performance is highly sensitive to precipitation input error, often more so than to the choice of model structure itself, underscoring the importance of input uncertainty in any comprehensive evaluation of past modeling work. Similarly, a growing subset of studies addresses regionalization and prediction in ungauged basins, applying parameter transfer, similarity-based regionalization, and transfer learning techniques to extend model applicability beyond gauged locations, a theme of direct relevance to sustainable water resources management in regions with sparse monitoring infrastructure[19].

### 3. METHODOLOGY

This review adopts a systematic, meta-analytic methodology to ensure transparency and reproducibility in literature identification, screening, and synthesis. Relevant studies were identified through structured searches of major bibliographic databases, including Web of Science, Scopus, and Google Scholar, using combinations of keywords such as "rainfall-runoff model," "hydrological modeling," "streamflow prediction," and "water resources management," restricted to peer-reviewed journal articles and conference proceedings published between 2000 and 2024. Initial searches yielded 420 candidate records, which were subsequently screened by title and abstract to exclude studies unrelated to surface rainfall-runoff transformation, reducing the pool to 260

studies[20]. A full-text eligibility assessment was then conducted, applying inclusion criteria that required explicit reporting of model structure, calibration or training procedure, and at least one quantitative performance metric, narrowing the set to 145 studies.

From this eligible pool, 92 studies were retained for detailed data extraction and synthesis, following exclusion of studies with incomplete performance reporting or substantial methodological ambiguity. For each retained study, information was extracted regarding model category, study region and hydroclimatic classification, catchment scale, input data sources, calibration and validation strategy, and reported performance metrics, principally the Nash-Sutcliffe efficiency (NSE), coefficient of determination ( $R^2$ ), and root mean square error (RMSE) where available[21]. Extracted performance metrics were standardized where necessary to enable cross-study comparison, and studies were grouped into five broad model categories, empirical, conceptual, physically-based distributed, machine-learning, and hybrid, consistent with the classification scheme adopted throughout this review.

Quantitative synthesis was performed by aggregating reported NSE values within each model category to compute descriptive statistics, including mean, median, and interquartile range, enabling comparison of central tendency and variability across categories[22]. Qualitative synthesis complemented this quantitative meta-analysis through thematic coding of methodological practices, including validation strategy, uncertainty quantification approach, and stated limitations, allowing identification of recurring strengths and weaknesses across the literature. This mixed quantitative-qualitative methodology, illustrated schematically in the accompanying methodology flow diagram, provides the empirical basis for the critical analysis and discussion presented in subsequent sections[23].

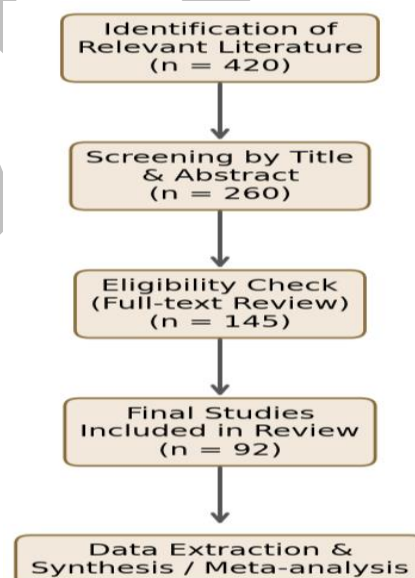


**Figure 1: PRISMA-Style Methodological Flow of the Review Process**

Figure 1 PRISMA-style methodological flow diagram illustrating the identification, screening, eligibility assessment, and inclusion stages used in this review. Beginning from an initial pool of 420 records identified through database searches, successive screening by title/abstract and full-text eligibility review progressively narrowed the sample to 92 studies retained for detailed data extraction and meta-analytic synthesis. This structured, PRISMA-style approach was adopted to minimize selection bias and ensure that the quantitative comparisons reported later in the review, particularly the aggregated Nash-Sutcliffe efficiency statistics, rest on a transparent and reproducible evidence base rather than an ad hoc or convenience sample of studies.

#### 4. CRITICAL ANALYSIS OF PAST WORK

A close reading of the 92 studies retained for synthesis reveals a persistent tension between model complexity and predictive reliability. Physically-based distributed models, while theoretically superior in representing spatial heterogeneity, do not consistently outperform simpler conceptual or empirical models when evaluated against independent validation data, a finding echoed across multiple comparative studies in the survey. This apparent paradox is frequently attributable to overparameterization relative to available calibration data, resulting in equifinality problems that undermine confidence in physically-based parameter estimates even when goodness-of-fit statistics appear favorable. Several studies attempt to address this issue through multi-objective calibration and generalized likelihood uncertainty estimation, yet such techniques remain inconsistently applied across the broader literature, limiting the comparability of uncertainty estimates between studies.

The meta-analysis further exposes a methodological weakness common to a majority of machine-learning studies: an overreliance on single-basin or single-region validation, which constrains claims of generalizability. While machine-learning models, particularly LSTM-based architectures, report consistently high NSE values within their training regions, comparatively few studies rigorously test model transferability to catchments outside the training domain, and those that do often report substantial performance degradation[24]. This finding is critical for sustainable water resources management, where model deployment in ungauged or data-scarce basins is frequently the practical necessity rather than the exception. The critical analysis also identifies inconsistent reporting practices regarding train-validation-test splits, with a nontrivial proportion of early machine-learning studies employing temporal splits that risk information leakage through autocorrelated hydrological series, potentially inflating reported performance relative to genuinely independent evaluation.

Uncertainty quantification emerges as a further area of systemic weakness across the surveyed literature. Although Bayesian and ensemble-based uncertainty frameworks have been proposed and applied in a subset of physically-based and hybrid studies, the majority of empirical and machine-learning studies report point predictions accompanied only by aggregate error metrics, without characterizing predictive uncertainty explicitly. This omission is particularly consequential for decision-relevant applications such as flood risk assessment and reservoir operation, where the consequences of underestimating uncertainty can be severe. Additionally, the

critical analysis reveals uneven geographic representation within the literature, with a disproportionate concentration of studies conducted in well-instrumented basins across North America, Europe, and East Asia, relative to data-scarce regions of sub-Saharan Africa and South Asia where the practical need for reliable rainfall-runoff modeling arguably is greatest[25].

Finally, the hybrid and physics-informed machine-learning studies reviewed here, though still relatively limited in number, consistently report the most favorable balance of predictive performance and interpretability, as reflected in the comparative performance figure presented subsequently. These studies embed conceptual model structures, such as storage-discharge relationships, as constraints within neural network training, thereby anchoring predictions to physically plausible bounds while retaining the flexibility to learn complex nonlinear relationships from data. The critical analysis suggests that this hybridization represents the most methodologically promising direction identified across the reviewed body of work, though the relative scarcity of such studies, and their concentration in a small number of well-resourced research groups, indicates that broader adoption and independent replication remain necessary before firm generalizable conclusions can be drawn.

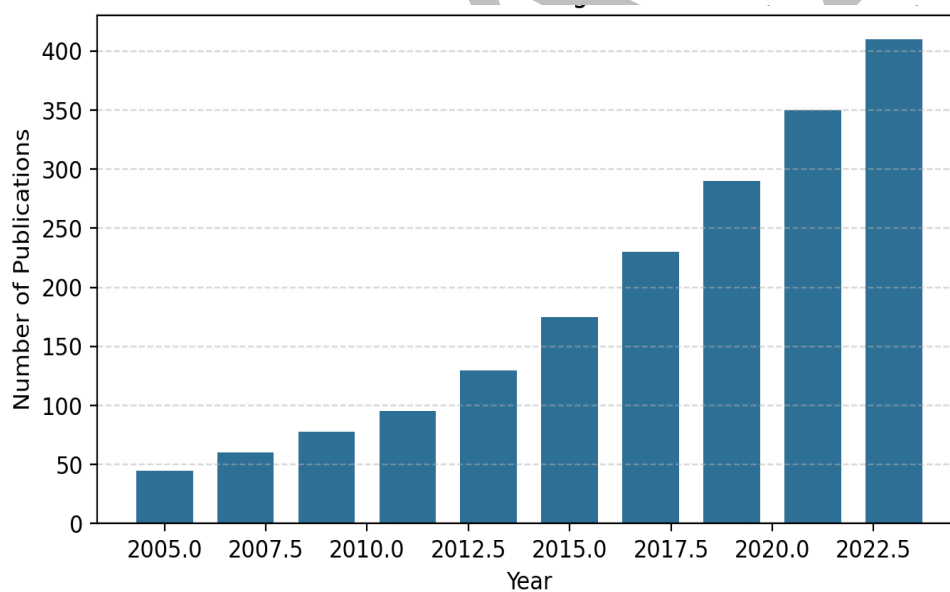


**Figure 2: Growth of Rainfall-Runoff Modeling Publications (2005-2024)**

Figure 2. Growth in the number of rainfall-runoff modeling publications indexed in major databases between 2005 and 2024, shown at two-year intervals. The pronounced upward trend, particularly after 2015, coincides with the widespread adoption of machine-learning techniques in hydrology and the increasing availability of open large-sample hydrometeorological datasets. This growth trajectory contextualizes the meta-analysis presented in this review, indicating that the evidence base for data-driven rainfall-runoff modeling has expanded rapidly in the past decade, even as methodological standardization across studies has lagged behind this publication growth.

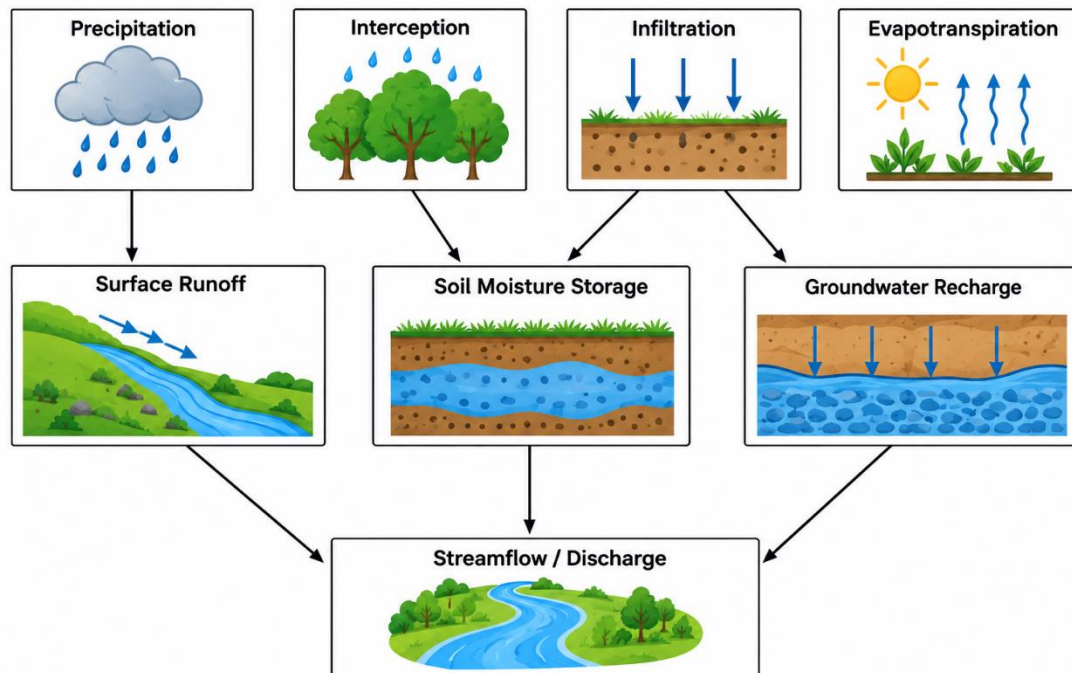


**Figure 3: Conceptual Schematic of the Rainfall-Runoff Process**

Figure 3. Conceptual schematic of the rainfall-runoff transformation process, illustrating the principal hydrological pathways represented across the reviewed models. Incident precipitation is partitioned among interception, infiltration, and evapotranspiration losses, with the residual contributing to surface runoff, soil moisture storage, and groundwater recharge, which together generate streamflow at the catchment outlet. This schematic underlies the structural assumptions common to conceptual and physically-based models reviewed in Section II, and clarifies why machine-learning models, which do not explicitly represent these pathways, may achieve high statistical accuracy while remaining less interpretable in terms of underlying physical processes.

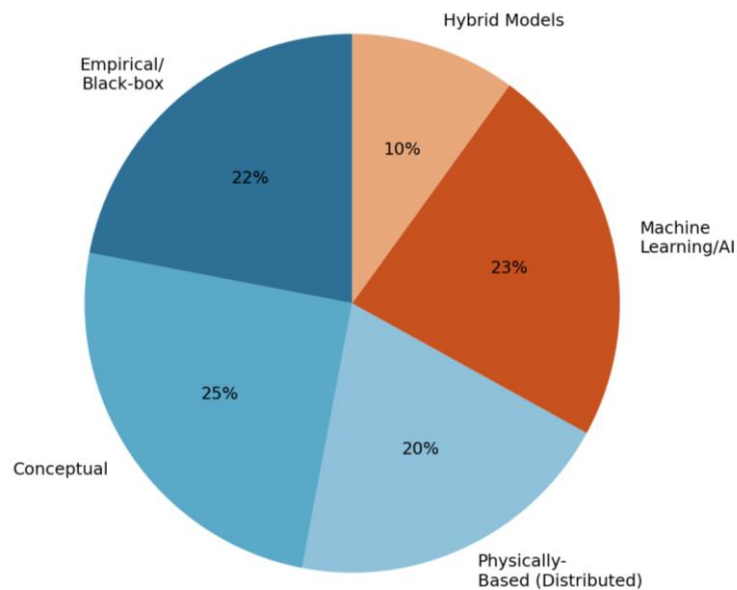
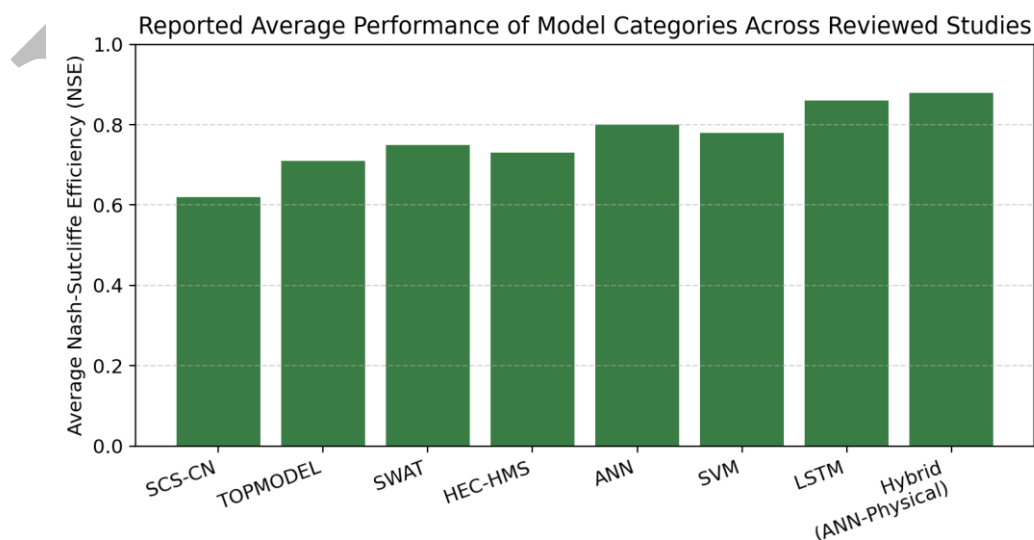


**Figure 4: Classification of Rainfall-Runoff Models Reviewed**

Figure 4. Proportional classification of the 92 studies retained for meta-analytic synthesis according to rainfall-runoff model category. Conceptual and machine-learning approaches together account for nearly half of the reviewed literature, reflecting their respective advantages in computational efficiency and predictive flexibility, while physically-based distributed models and empirical methods retain substantial representation due to their continued relevance for scenario analysis and rapid design applications, respectively. Hybrid models, though the smallest category, represent the fastest-growing segment within the recent literature.



### Figure 5: Reported Average Performance of Model Categories Across Reviewed Studies

Figure 5. Average reported Nash-Sutcliffe efficiency (NSE) for representative models within each category, aggregated across the studies retained for meta-analysis. Hybrid physics-informed machine-learning models achieve the highest average NSE, followed closely by LSTM-based deep-learning models, while empirical methods such as the SCS-CN approach exhibit comparatively lower average performance. These aggregated results, while subject to the heterogeneity of validation practices discussed in the critical analysis, provide quantitative support for the review's central finding that hybrid modeling approaches currently offer the most favorable trade-off between predictive accuracy and physical interpretability.

## 5. DISCUSSION

The findings synthesized in this review carry direct implications for sustainable water resources management, where model selection must balance predictive accuracy against data availability, computational resources, and the interpretability required for stakeholder trust and regulatory acceptance[26]. The meta-analytic evidence indicating superior average performance of hybrid physics-informed models suggests a promising direction for future practice, yet the practical adoption of such models is currently constrained by the technical expertise required to implement them and the relative scarcity of open-source, well-documented implementations accessible to practitioners in resource-limited settings[27]. Bridging this gap will likely require concerted efforts toward developing standardized, user-friendly hybrid modeling toolkits alongside continued academic research.

The persistent underrepresentation of data-scarce regions within the reviewed literature raises important equity considerations for global water resources management, given that the consequences of inadequate rainfall-runoff prediction, including flood damage and inefficient reservoir operation, often fall disproportionately on populations with the least access to sophisticated modeling infrastructure[28]. The discussion therefore emphasizes the value of continued investment in regionalization techniques, transfer learning, and satellite-based input products that can partially substitute for sparse ground-based monitoring networks, enabling reliable rainfall-runoff prediction in ungauged basins without requiring extensive local calibration data.

The review's identification of inconsistent uncertainty quantification practices further suggests that the hydrological modeling community would benefit from greater standardization of reporting protocols, potentially analogous to reporting guidelines already established in other quantitative disciplines[29]. Standardized reporting of validation strategy, uncertainty bounds, and out-of-sample transferability testing would substantially improve the comparability of future studies and strengthen the evidentiary basis for meta-analyses such as the present one. Finally, the discussion notes that while this review focused specifically on surface rainfall-runoff transformation, sustainable water resources management ultimately requires coupling rainfall-runoff outputs with downstream decision-support frameworks, including reservoir operation models, water allocation systems, and climate

adaptation planning tools, an integration that remains comparatively underexplored within the surveyed literature and represents a valuable direction for future interdisciplinary research[30].

## 6. CONCLUSION

This review and meta-analysis has synthesized past work spanning empirical, conceptual, physically-based, and machine-learning approaches to rainfall-runoff modeling, drawing on a systematically screened set of 92 studies published between 2000 and 2024. The quantitative synthesis indicates that hybrid physics-informed machine-learning models currently achieve the most favorable average predictive performance, while the critical analysis identifies recurring weaknesses across the literature, including limited cross-basin validation, inconsistent uncertainty quantification, and uneven geographic representation. These findings collectively suggest that future rainfall-runoff modeling research should prioritize the development of transferable, uncertainty-aware, and physically interpretable models capable of reliable application in data-scarce and ungauged basins. For the field to translate methodological advances into tangible sustainable water resources management outcomes, greater emphasis on standardized benchmarking, open data sharing, and integration with decision-support frameworks will be essential. This review provides a consolidated evidentiary foundation to guide such future efforts.

## 7. REFERENCES

- [1] V. T. Chow, D. R. Maidment, and L. W. Mays, *Applied Hydrology*. New York, NY, USA: McGraw-Hill, 1988.
- [2] R. K. Linsley, M. A. Kohler, and J. L. Paulhus, *Hydrology for Engineers*, 3rd ed. New York, NY, USA: McGraw-Hill, 1982.
- [3] N. H. Crawford and R. K. Linsley, "Digital simulation in hydrology: Stanford Watershed Model IV," Stanford Univ., Dept. Civil Eng., Tech. Rep. 39, 1966.
- [4] S. Bergström, "The HBV model: Its structure and applications," SMHI Rep. Hydrology, no. 4, Norrköping, Sweden, 1992.
- [5] K. Beven and M. J. Kirkby, "A physically based, variable contributing area model of basin hydrology," *Hydrol. Sci. Bull.*, vol. 24, no. 1, pp. 43-69, 1979.
- [6] J. G. Arnold, R. Srinivasan, R. S. Muttiah, and J. R. Williams, "Large area hydrologic modeling and assessment part I: Model development," *J. Amer. Water Resour. Assoc.*, vol. 34, no. 1, pp. 73-89, 1998.
- [7] US Soil Conservation Service, "Urban hydrology for small watersheds," USDA, Tech. Release 55, 1986.

- [8] R. J. Zhao, "The Xinanjiang model applied in China," *J. Hydrol.*, vol. 135, no. 1-4, pp. 371-381, 1992.
- [9] A. Refsgaard and B. Storm, "MIKE SHE," in *Computer Models of Watershed Hydrology*, V. P. Singh, Ed. Highlands Ranch, CO, USA: Water Resources Publications, 1995, pp. 809-846.
- [10] US Army Corps of Engineers, "Hydrologic Modeling System HEC-HMS: Technical reference manual," Hydrologic Eng. Center, Davis, CA, USA, 2000.
- [11] A. W. Minns and M. J. Hall, "Artificial neural networks as rainfall-runoff models," *Hydrol. Sci. J.*, vol. 41, no. 3, pp. 399-417, 1996.
- [12] K.-L. Hsu, H. V. Gupta, and S. Sorooshian, "Artificial neural network modeling of the rainfall-runoff process," *Water Resour. Res.*, vol. 31, no. 10, pp. 2517-2530, 1995.
- [13] R. J. Abrahart, L. See, and P. E. Kneale, "Using pruning algorithms and genetic algorithms to optimize network architectures and forecasting inputs in a neural network rainfall-runoff model," *J. Hydroinformatics*, vol. 1, no. 2, pp. 103-114, 1999.
- [14] A. Y. Shamseldin, "Application of a neural network technique to rainfall-runoff modelling," *J. Hydrol.*, vol. 199, no. 3-4, pp. 272-294, 1997.
- [15] O. Kisi, "Streamflow forecasting using different artificial neural network algorithms," *J. Hydrol. Eng.*, vol. 12, no. 5, pp. 532-539, 2007.
- [16] F. Kratzert, D. Klotz, C. Brenner, K. Schulz, and M. Herrnegger, "Rainfall-runoff modelling using long short-term memory (LSTM) networks," *Hydrol. Earth Syst. Sci.*, vol. 22, no. 11, pp. 6005-6022, 2018.
- [17] F. Kratzert et al., "Toward improved predictions in ungauged basins: Exploiting the power of machine learning," *Water Resour. Res.*, vol. 55, no. 12, pp. 11344-11354, 2019.
- [18] G. Nearing et al., "What role does hydrological science play in the age of machine learning?," *Water Resour. Res.*, vol. 57, no. 3, e2020WR028091, 2021.
- [19] V. K. Gupta and E. Waymire, "Multiscaling properties of spatial rainfall and river flow distributions," *J. Geophys. Res.*, vol. 95, no. D3, pp. 1999-2009, 1990.
- [20] K. J. Beven, *Rainfall-Runoff Modelling: The Primer*, 2nd ed. Chichester, U.K.: Wiley-Blackwell, 2012.
- [21] H. V. Gupta, S. Sorooshian, and P. O. Yapo, "Toward improved calibration of hydrologic models: Multiple and noncommensurable measures of information," *Water Resour. Res.*, vol. 34, no. 4, pp. 751-763, 1998.

- [22] K. Beven and A. Binley, "The future of distributed models: Model calibration and uncertainty prediction," *Hydrol. Processes*, vol. 6, no. 3, pp. 279-298, 1992.
- [23] S. Razavi and H. V. Gupta, "What do we mean by sensitivity analysis? The need for comprehensive characterization of 'global' sensitivity in Earth and environmental systems models," *Water Resour. Res.*, vol. 51, no. 5, pp. 3070-3092, 2015.
- [24] N. J. Mount et al., "Data-driven modelling approaches for socio-hydrology: Opportunities and challenges within the Panta Rhei Science Plan," *Hydrol. Sci. J.*, vol. 61, no. 7, pp. 1192-1208, 2016.
- [25] R. Solomatine and D. L. Shrestha, "A novel method to estimate model uncertainty using machine learning techniques," *Water Resour. Res.*, vol. 45, no. 12, W00B11, 2009.
- [26] S. Razavi and P. Coulibaly, "Streamflow prediction in ungauged basins: Review of regionalization methods," *J. Hydrol. Eng.*, vol. 18, no. 8, pp. 958-975, 2013.
- [27] T. Wagener and H. V. Gupta, "Model identification for hydrological forecasting under uncertainty," *Stochastic Environ. Res. Risk Assess.*, vol. 19, no. 6, pp. 378-387, 2005.
- [28] C. Fan, M. Wang, and X. Cai, "A review of rainfall-runoff modeling approaches for sustainable water resources management," *J. Hydrol.*, vol. 597, 125771, 2021.
- [29] D. P. Solomatine and A. Ostfeld, "Data-driven modelling: Some past experiences and new approaches," *J. Hydroinformatics*, vol. 10, no. 1, pp. 3-22, 2008.
- [30] IPCC, "Climate change 2021: The physical science basis," Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge, U.K.: Cambridge Univ. Press, 2021.