



Unleashing the power of AI: revolutionizing runoff prediction beyond NRCS-CN method

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Received: 18 January 2024 / Accepted: 18 June 2024 / Published online: 26 June 2024
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Abstract

Predicting runoff is vital for effectively planning and managing water resources within a watershed or river basin. This research aims to compare the effectiveness of two distinct approaches in predicting daily runoff within the Koyna River basin in India from 1999 to 2011. The approaches examined are an artificial intelligence-based data-driven model, specifically an artificial neural network (ANN), and a conceptual-based model, the Natural Resource Conservation Service Curve Number (NRCS-CN) method. The ANN model employs a data-driven approach that utilizes historical runoff data to train the model, allowing it to capture nonlinear relationships and complexities in runoff dynamics. In contrast, the NRCS-CN method uses a conceptual-based approach, relying on empirical relationships and soil cover complex data to estimate runoff. The performance of both models was evaluated using the coefficient of determination (R^2) as a key metric. The study highlights a significant difference in predictive performance between the two methodologies. The NRCS-CN method achieved an R^2 of 0.37, whereas the ANN model significantly improved the predictive accuracy, achieving an R^2 of 0.88. This substantial increase demonstrates the ANN model's superior ability to capture the complexities of daily runoff dynamics compared to the NRCS-CN method. In conclusion, the findings strongly advocate for the efficacy of the data-driven ANN model over the conceptual-based NRCS-CN model for daily runoff prediction. The superior performance of the ANN model provides valuable insights for enhancing water resource management through advanced artificial intelligence techniques. These results suggest that integrating AI-driven models can significantly improve the accuracy and reliability of runoff predictions, thereby supporting more effective water resource planning and management.

Keywords ANN · NRCS-CN · Watershed planning and management · Gamma test

Introduction

The rapid growth rate of the Indian population emphasizes the crucial need for accurate management of natural resources, encompassing both land and water, to adequately fulfill the daily needs of this expanding population (Tarate and Awari 2018; Rabiei et al. 2022). Improper utilization and excessive exploitation of natural resources contribute to the degradation of these valuable assets. In the context of watershed management and planning, there is a heightened focus on the conservation and prudent utilization of

water resources (Ghashghaie et al. 2022). The assessment of available water resources for diverse purposes is integral to urban planning, land use/land cover planning, and flood and drought management (Sarkar and Pandey 2015, Shiri et al. 2018, Javadinejad et al. 2019a). Accurate assessment of the portion of rainfall that transforms into surface runoff stands as a pivotal aspect within hydrological engineering and watershed management (Verma et al. 2017). Predicting how much water will flow in rivers helps us to create systems that warn us early about floods, making it easier to manage and predict them (Javadinejad et al. 2019b). Predicting runoff is crucial for managing floods, and it is just as important for preparing and managing droughts. Hydrological processes, such as the rainfall-runoff process, exhibit considerable complexity owing to the spatio-temporal variability of various incorporating variables. Diverse categories of models, spanning from physical models to data-driven alternatives like ANNs, are accessible for rainfall-runoff modeling. However,

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physical models necessitate an extensive amount of data, including detailed field data, resulting in a time-consuming endeavor to achieve predefined objectives (Senaviratne et al. 2014). Models like ANNs use artificial intelligence systems created to imitate how the human brain functions. Given the highly non-linear and non-stationary nature of hydrological processes, ANNs demonstrate superior capabilities in capturing these complexities compared to other models. Consequently, ANN stands out as a notable non-linear tool for predicting hydrological behavior (Burgan 2022). It possesses considerable potential for modeling the non-linear complexities inherent in process behavior. Conceptual models reside between the realms of the black box (data-driven) and physical models, grounded in specific assumptions and conceptual frameworks. Chavan and Ukarande (2017) employed the ANN technique to predict runoff 1 day ahead in the Amba River basin of India. They suggested that ANN models have emerged as robust tools for modeling the rainfall-runoff relationship. Aoulmi et al. (2021) examined the feasibility of employing ANNs with diverse input configurations to characterize the rainfall-runoff relationship within the Seybouse basin situated in a semi-arid region of Algeria. They advocated for the use of ANN models in rainfall-runoff modeling due to their straightforward structures and high precision, enabling effective resolution of issues about water resource management.

The NRCS-CN method, alternatively known as the SCS-CN method, stands as a conceptual approach formulated for the estimation of runoff in small agricultural watersheds (Singh and Satapathy 2017). It takes into account various climatic and catchment characteristics, encompassing soil data, land use/land cover, slope of the land surface, and antecedent moisture conditions (Gayathri and Jayalakshmi 2018). This method's simplicity lies in its reliance solely on the curve number (CN) values associated with the basin area (Rawat and Singh 2017; Bajirao and Kumar 2022). Remote sensing and GIS can be readily utilized for estimating the curve number (Siddi et al. 2018). Due to its straightforward nature, various models like SWAT and CREAMS are integrated with the NRCS-CN method for estimating runoff. Farran and Elfeki (2020) studied the actual values of CN in the Saudi Arabian arid basin and found that the CN varies between 45 and 85. Meshram et al. (2017) suggested that remote sensing and GIS represent highly reliable techniques for generating the majority of input data necessary for the NRCS-CN model for runoff estimation. Akbari et al. (2021) applied the NRCS-CN method for rainfall-runoff modeling in the Kardeh watershed of Iran and observed a strong correlation between actual and estimated direct runoff. Sishah (2021) utilized a GIS-based NRCS-CN runoff simulation model to estimate surface runoff for the Awash River basin in Ethiopia. Validation results indicated a strong correlation between predicted and observed runoff, affirming the

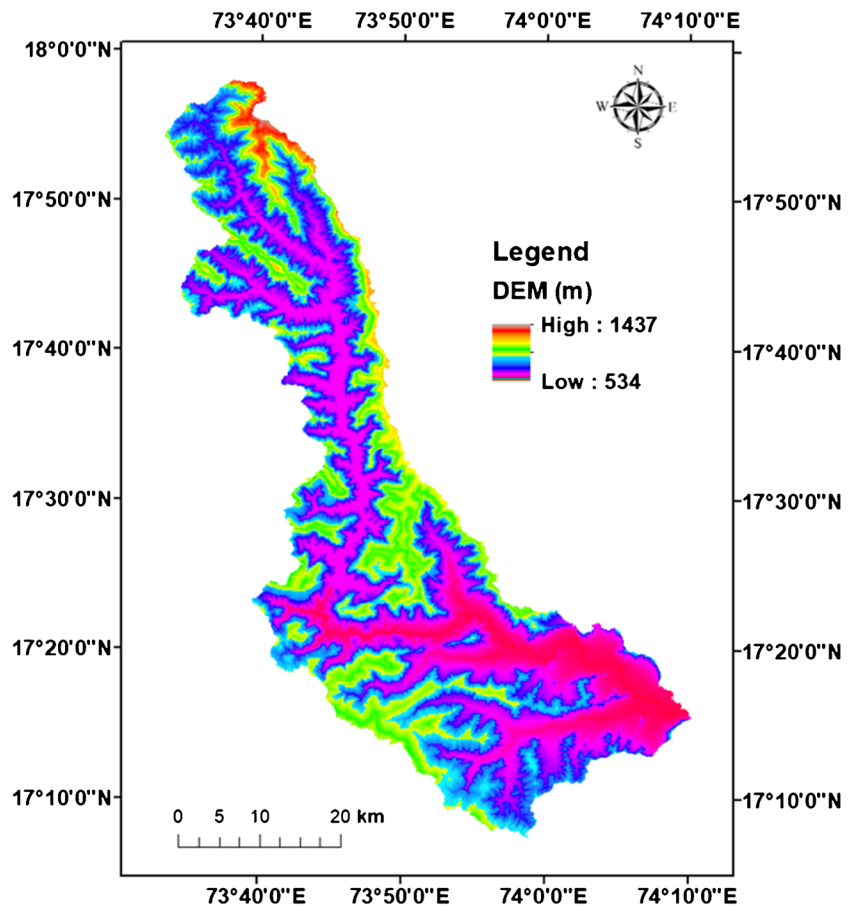
model's accuracy. Trivedi and Awasthi (2021) estimated runoff by integrating the GIS and NRCS-CN methods for the Kanari River Watershed of Madhya Pradesh in India. They proposed that the combination of the curve number method with remote sensing and GIS techniques is highly effective and efficient for simulating rainfall-runoff processes and determining total surface runoff. Gupta and Dixit (2022) utilized the GIS-based NRCS-CN method to estimate surface runoff in the Assam region of India. Their findings suggest that the NRCS-CN model proves to be effective and dependable for this region, with potential applicability to other areas prone to waterlogging under heavy rainfall conditions. Mandal and Biswas (2021) predicted surface runoff using ANN and NRCS-CN methods in the Mayurakshi River Catchment of India. They observed that the ANN model demonstrates superior efficiency in predicting runoff within a shorter timeframe compared to the NRCS-CN method. Praveen et al. (2016) applied empirical methods like NRCS-CN methods and artificial intelligence-based fuzzy logic models for runoff estimation. They revealed that artificial intelligence-based models provide promising results for runoff estimation. Sivaprakasam et al. (2018) proposed that the NRCS-CN method requires abundant field data, including topography, soil type, and moisture conditions which may not always be readily accessible. Prasanna et al. (2023) predicted and compared runoff using analytical NRCS-CN and mathematical data-driven ANN models. They suggested that in the future, ANNs are likely to gain increased acceptance among hydrologists due to their interpretative and predictive capabilities. Therefore, this study is carried out to search for an alternative to the conceptual NRCS-CN method for runoff prediction. To the best of our knowledge, very limited research is available in the literature comparing artificial intelligence and conceptual runoff prediction models. Consequently, with the consideration of these factors, an effort has been undertaken to assess the comparative predictive capabilities of the data-driven model (i.e., ANN) and the conceptual-based model (i.e., NRCS-CN) for runoff estimation in the selected study area.

Material and methods

Study area

The Koyna River which is a tributary of the Krishna River flows through the Satara district of Maharashtra, India. The study area is situated in a subtropical climate, which is characterized by a significant portion of rainfall during the monsoon season. The topographic elevation of the areal expanse in the study area is shown in Fig. 1. The soil in the study area is light laterite and black cotton type. The majority of livelihoods within this basin depend on agriculture to fulfill

Fig. 1 Geographical location of Koyna River basin



their daily needs. The entire basin encompasses agricultural land, bare land, open forest land, built-up areas, dense forest land, and water bodies.

Data collection

We collected daily rainfall data from June to September, covering the years from 1999 to 2011, from the Agriculture Department of Maharashtra state. Similarly, the daily run-off data for the same period was obtained from the Central Water Commission, New Delhi. We collected the ASTER DEM and Landsat 7 satellite data from the United States Geological Survey (USGS) website. For creating a soil map of the study area, we used the FAO soil map data.

ANN

The ANN model is like a network of connected brain cells, trying to mimic how our brain works. This model has different layers, such as the input layer where it gets information, hidden layers that help connect the input and output, and the output layer which gives the final result. Figure 2 shows how this model looks with one hidden layer. Just like our brain,

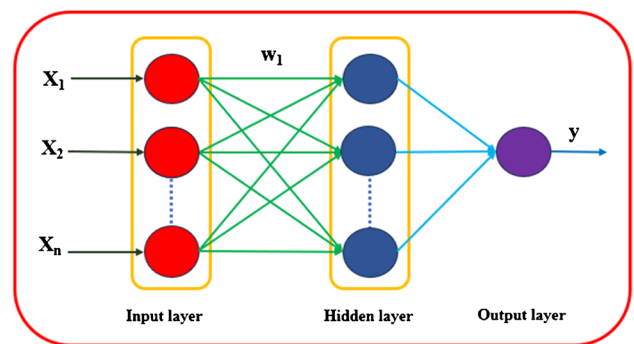


Fig. 2 ANN architecture with one hidden layer

this model changes the information it gets (inputs x) into the results we want (outputs y).

$$y = f(u_i) \tag{1}$$

In Eq. (1), the variable y is a function of u_i . The function $f(\cdot)$ represents the transfer function, depicting a neuron's response to its total input. Various transfer functions, such as hyperbolic tangent or sigmoid, exist. In this investigation, the sigmoid transfer function was employed in the creation

of different Multilayer Perceptron (MLP) ANN models, implemented using MATLAB (R2015a) software. The net function (u_i) calculated at each neuron can be expressed as given in Eq. (2):

$$u_i = \sum (W_i X_i - \theta_i) \quad (2)$$

Here, W represents the weight assigned to the input variable X and θ is the threshold value or bias. A training process is implemented to determine the optimal weights, as shown in Eq. (2). The goal of the training process is to make sure the model gives results that are very similar to the expected values, which are the ones we measured. Various training algorithms are available across different fields. In this investigation, the Levenberg–Marquardt transfer function, which utilizes a back-propagation algorithm, was employed. In the back-propagation algorithm, the error is computed by comparing the model-generated output with the target values, and this determined error facilitates the adjustment of connection weights. This repeated process keeps happening until the network converges into a steady and unchanging condition. The training process was concluded after reaching a maximum of 1000 epochs (iterations) with a training threshold of 0.001. In this study, feed-forward MLP-based ANN models were trained and tested using the nntool in MATLAB (R2015a) software. Specifically, three-layered neural network models consisting of one input layer, one hidden layer, and one output layer were employed for prediction purposes. The hyperbolic tangent sigmoid (tansig) transfer function was utilized, which is commonly employed for addressing complex problems.

NRCS-CN method

This approach is a concept created specifically for figuring out how much water runs off in small watershed areas. It operates on two key assumptions: first, the initial abstraction (I_a) is some fraction of the potential maximum retention (S), and second, the ratio of actual runoff (Q) to potential maximum runoff ($P - I_a$) is equivalent to the ratio of actual infiltration (F) to potential maximum retention (S). Through the integration of these assumptions, the NRCS-CN method simplifies the runoff estimation equation as,

$$Q = \frac{(P - \lambda S)^2}{(P + (1 - \lambda)S)} \quad (3)$$

In the context of Indian conditions, the recommended values for λ are 0.1 and 0.3, dependent on soil type and the cumulative rainfall over the preceding 5 days. The NRCS-CN method relies on several key input data, including the delineation of watershed boundaries, the creation of hydrological soil group (HSG) maps, the development of land use and land cover (LULC) maps, and the selection of the Antecedent Moisture Condition (AMC) to calculate daily runoff. The methodology employed in this study is depicted in Fig. 3, illustrating the runoff computation flowchart. Initially, all necessary data were collected from various sources. Thematic maps like LULC and HSG were created. HSGs were classified into A, B, C, and D based on soil texture and infiltration rates. The LULC map was generated using Landsat satellite images, while the HSG map was derived from the FAO soil map of the world. Subsequently,

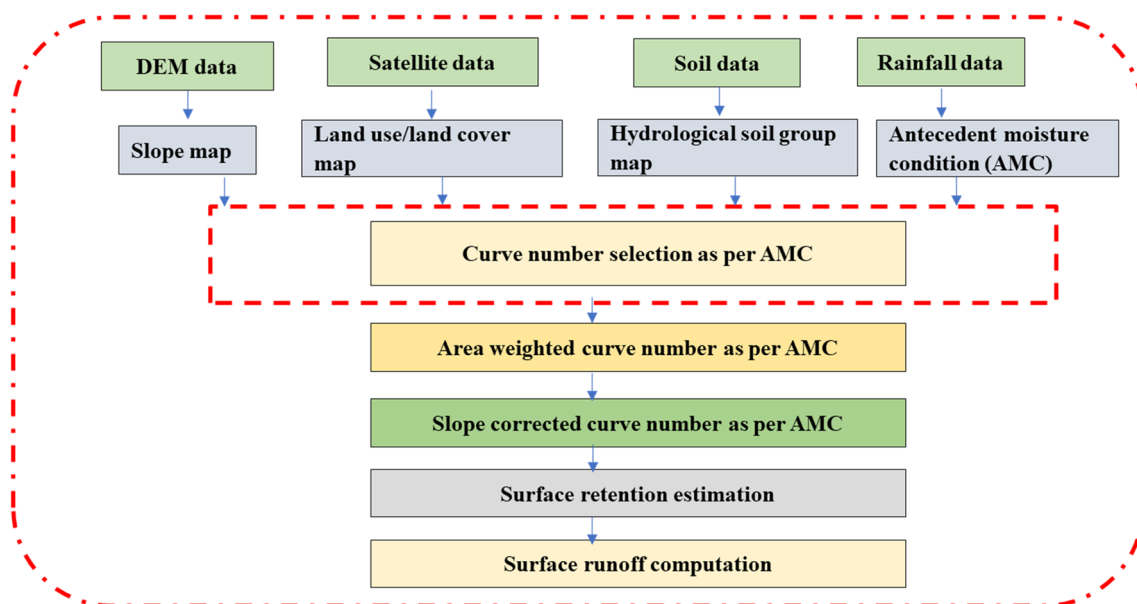


Fig. 3 Flowchart showing methodology used for runoff prediction using the NRCS-CN method

the LULC map was overlaid onto the HSG map within a GIS environment. Individual polygons representing LULC and corresponding HSG were delineated using the intersect tool in ArcGIS 10.2 software. The area of each polygon was calculated, and a curve number value was assigned based on the combination of LULC and HSG. The weighted curve number for the entire study area was determined by considering all LULC-HSG polygons and was used to compute runoff generated across the entire study area. Finally, the runoff from the study area was computed using corresponding rainfall data. Detailed information about the NRCS-CN method is available in Verma et al. (2017).

Performance evaluation of ANN models and NRCS-CN method

Correlation coefficient (r)

It measures how well the predicted runoff matches with what we observe.

$$r = \left[\frac{\sum_{i=1}^n \{ (Q_o - \bar{Q}_o)(Q_p - \bar{Q}_p) \}}{\sqrt{\sum_{i=1}^n (Q_o - \bar{Q}_o)^2} \sqrt{\sum_{i=1}^n (Q_p - \bar{Q}_p)^2}} \right] \quad (4)$$

where Q_o and Q_p indicate the observed and predicted values, respectively. \bar{Q}_o and \bar{Q}_p are the average of observed and predicted values, respectively.

Coefficient of determination (R^2)

It indicates how much of the change in the thing we are studying (dependent variable) is clarified by the things we are measuring (independent variables). Higher values of both r and R^2 indicate superior performance of the runoff prediction model.

The flowchart of the methodology adopted for comparison of both approaches for runoff prediction in the study area is shown in Fig. 4.

Result and discussion

Various statistical parameters of the time series dataset utilized in this analysis for rainfall-runoff modeling are presented in Table 1 for rainfall-runoff modeling. The time series of the rainfall and runoff dataset used in this analysis is shown in Fig. 5. The dataset was divided into two parts: the first 70% of the data was allocated for training, and the remaining 30% was used for testing the developed models. Throughout both the training and testing periods,

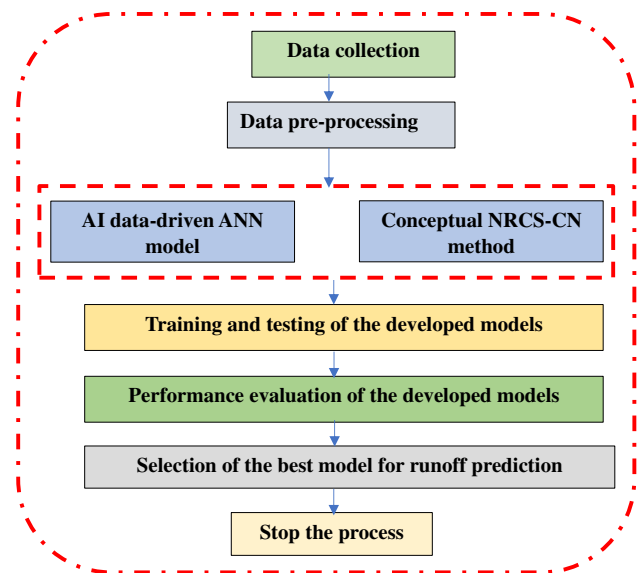


Fig. 4 Flowchart of the methodology used for runoff prediction

lower skewness values were observed in both datasets. It is crucial for effective modeling that skewness values remain low, as higher values can significantly impact the performance of developed models (Bajirao et al. 2021b). Furthermore, the maximum and minimum values of rainfall (160.08 and 0 mm) and runoff (3124.73 and 0 m³/s) within the testing dataset fall within the limits observed in the training dataset for rainfall (198.39 and 0 mm) and runoff (4972.54 and 0 m³/s), respectively. This observation ensures that the trained models encounter no difficulties when extrapolating data.

In the development of various ANN models, the optimal input combination is determined by selecting inputs with the minimum gamma value. The Gamma test functions as the criterion for determining the most efficient input variables (Bajirao et al. 2021a). This analysis underscores the importance of incorporating present-day rainfall, along with rainfall from the preceding 1 and 2 days, as well as the preceding 1-day runoff, to accurately predict today's runoff. So, these factors were important, and we used them in making different ANN models. We developed a total of 20 ANN models by changing the number of neurons in a hidden layer, starting from 1 and going up to 20. Among these models, the ANN-16, characterized by an architecture of (4–16–1), emerged as the most favorable based on statistical performance criteria, specifically exhibiting higher r and R^2 values during the testing period. The superior predictive capabilities of the selected ANN-16 model are visually represented in Fig. 6 through time series and scatter plot analysis. The assessment of the ANN-16 model for daily runoff prediction revealed its commendable performance, as evidenced by r and R^2 values of 0.94 and 0.88, respectively.

Table 1 Statistical parameters of the dataset used for daily runoff prediction

Statistical parameters	Whole data		Training data		Testing data	
	R_t (mm)	Q_t (m ³ /s)	R_t (mm)	Q_t (m ³ /s)	R_t (mm)	Q_t (m ³ /s)
Mean	15.77	246.72	16.42	268.34	14.27	196.44
Median	5.94	99.81	6.35	99.93	7.00	123.06
Standard deviation	24.70	448.84	25.56	499.49	22.54	294.04
Coefficient of variation (%)	156	181	155	186	157	149
Kurtosis	11.22	30.52	10.79	26.00	12.04	29.96
Skewness	2.96	4.70	2.91	4.40	3.05	4.54
Range	198.39	4972.54	198.39	4972.54	160.08	3124.73
Minimum	0.00	0.00	0.00	0.00	0.00	0.00
Maximum	198.39	4972.54	198.39	4972.54	160.08	3124.73

Fig. 5 Rainfall and runoff time series data used for daily runoff prediction

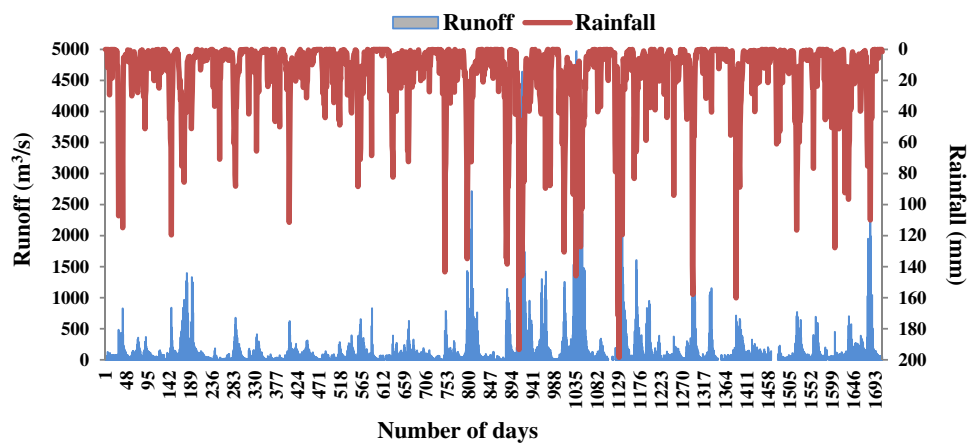
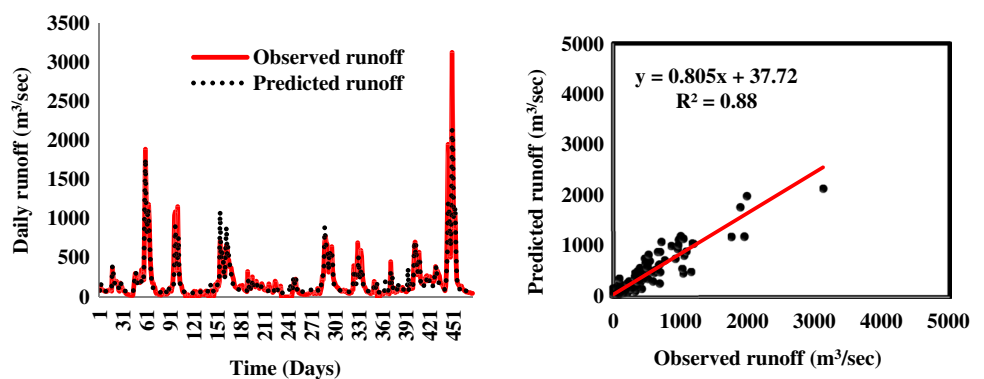


Fig. 6 Predictive performance of ANN-16 model for daily runoff prediction during testing



In alignment with our findings, Mohseni and Muskula (2023) reported a correlation coefficient (r) of 0.95 for the prediction of runoff using ANN in the Purna Sub-Catchment located within the Upper Tapi Basin of India. Turhan (2021) conducted a comparison of various ANN models utilizing different transfer functions at the Nergizlik Dam in Turkey. They noted that ANN methods exhibited statistically significant outcomes in rainfall-runoff modeling, suggesting that the developed models can effectively estimate average monthly flows. Chebii et al. (2022) utilized ANN for flood prediction in the Perkerra catchment of Kenya and noted a

correlation coefficient (r) of 0.949, indicating a strong relationship between input and output values. The study highlights that an ANN can accurately and reliably predict river runoff without requiring resource-intensive or complex additional data, thus offering a valuable solution to water-related challenges across various hydrological domains. Varughese et al. (2022) modeled the non-linear rainfall-runoff process of the Bharathapuzha River basin of India using data-driven ANN and compared it with a semi-distributed, physically based SWAT model. Ultimately, the study indicated that the performance of the ANN models was satisfactory,

suggesting that the ANN model could be applied for runoff prediction in regions with limited data availability.

The evaluation of the NRCS-CN method’s performance in estimating surface runoff was assessed qualitatively. The results indicated that the NRCS-CN method is applicable for estimating daily surface runoff, as evidenced by some degree of agreement between predicted and observed runoff depicted in Fig. 7. However, the predictive accuracy of the NRCS-CN method in daily runoff prediction revealed suboptimal performance, as indicated by low values of r and R^2 , specifically observed to be 0.61 and 0.37, respectively. Figure 6 visually depicts the predictive performance of the NRCS-CN method through time series and scatter plots. Remarkably, the NRCS-CN method displays a tendency to either underpredict or overpredict extreme (higher) values of daily surface runoff. The predictive performance of NRCS-CN and ANN models is also depicted in Fig. 8 through a violin plot. Here, it is evident that the ANN model can capture the overall shape of the actual observed runoff, indicating its superior predictive performance.

Similar to our findings, Pathan and Joshi (2019) found that the result of simulated annual runoff using linear regression is more accurate with the observed annual runoff in comparison to the simulated annual runoff using the NRCS-CN model. Ebrahimian et al. (2012) assessed the suitability of integrating the NRCS-CN method with GIS for estimating runoff depth in a mountainous watershed in Iran. The findings revealed a relatively low Nash–Sutcliffe efficiency, with a fair correlation ($r=0.56$) between estimated and observed runoff depth. These results suggest that the combined approach of GIS and the NRCS-CN method can be applied in semi-arid mountainous watersheds primarily for management and conservation purposes. Prasanna et al. (2023) proposed that data-driven ANN models demonstrate superior efficiency and accuracy in comparison to analytical NRCS-CN methods. The NRCS-CN method concentrates on the estimation of daily runoff potential resulting from rainstorms, neglecting to incorporate the influence of

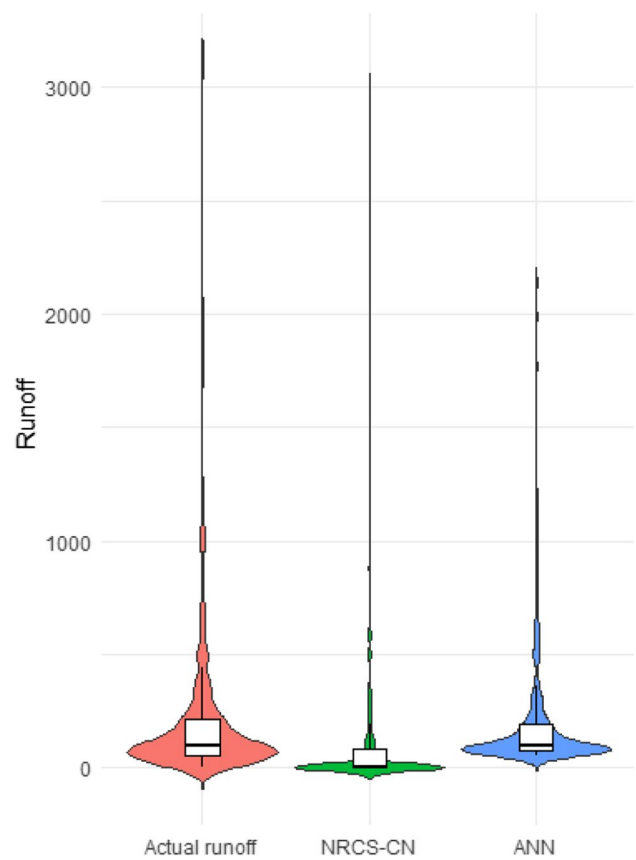
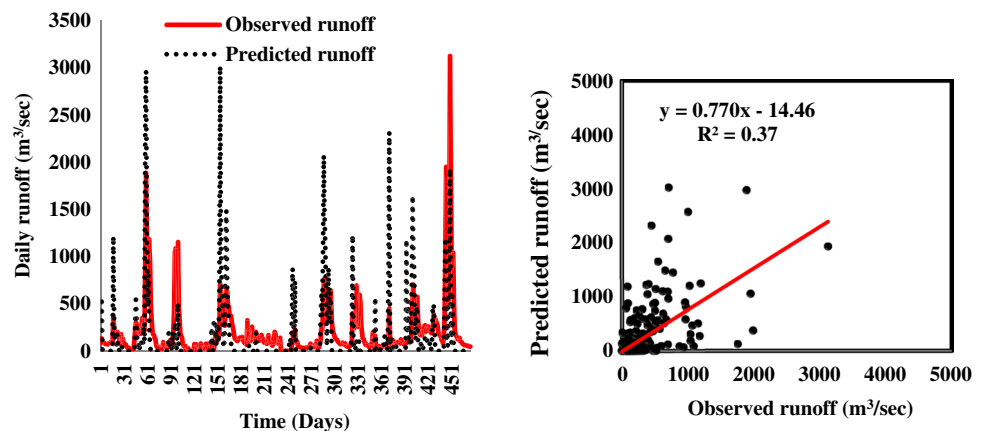


Fig. 8 Violin plot showing predictive performance of both NRCS-CN and ANN models

Fig. 7 Predictive performance of NRCS-CN method for daily runoff prediction during validation



antecedent moisture within its fundamental framework. It does not consider the influence of rain intensity and duration. Furthermore, it lacks explicit provisions for addressing the spatial variability of rainfall. It functions as an event-based model rather than a continuous simulation model. The NRCS-CN method implicitly assumes that infiltration excess is the dominant runoff mechanism, overlooking the contribution of the saturation excess mechanism. It performs

optimally on agricultural sites, moderately on range sites, and inadequately on humid, semi-arid climatic, and forested regions (Verma et al. 2017). When predicting runoff, various models require different datasets including land use patterns, soil properties, slope distributions, temperature fluctuations, rainfall amounts, and changes in river stage over time. However, obtaining all the necessary data for a catchment area can be challenging. Constructing a hydrological model in an ungauged region can be difficult due to the cost and complexity of data collection procedures (Mandal and Biswas 2021). Bhadra et al. (2010) compared the rainfall-runoff modeling performance of the semi-distributed conceptual NRCS-CN method to that of the ANN technique for Kangsabati catchment of West Bengal, India. The results indicated that for the Kangsabati catchment, the AI-based runoff prediction approach using the ANN technique, despite requiring significantly less data, predicted daily runoff values more accurately than the semi-distributed conceptual runoff prediction approach using the NRCS-CN method. Rawat et al. (2020) estimated runoff from ungauged agricultural watersheds with the NRCS-CN method and empirical mathematical models were compared with the NRCS-CN method. Merizalde et al. (2023) integrated geographic data and the NRCS-CN method with long short-term memory (LSTM) networks for enhancing runoff forecasting in a complex mountain Jubones basin. Asadi et al. (2019) demonstrated that incorporating hydro-geomorphic and biophysical time series inputs significantly enhances the accuracy of monthly runoff estimations using ANN data-driven models, highlighting their value for water resources planning and management. Adnan et al. (2020) and Adnan et al. (2021) modeled short-term rainfall-runoff using various machine-learning models alongside a conceptual event-based model. The comparison revealed that machine learning methods generally outperformed the conceptual event-based model in terms of predictive accuracy. Behfar et al. (2024) evaluated rainfall-runoff models for climate change studies using both conceptual and artificial intelligence approaches. They suggested that employing ensemble techniques, which combine conceptual and AI models, can improve the performance of rainfall-runoff modeling in the context of climate change. Kwon et al. (2020) employed a hybrid approach that integrates conceptual hydrological models, machine learning, and remote sensing data for rainfall-runoff modeling. They suggested that this framework could be advantageous and applicable to various hydrologic applications. Meresa (2019) modeled river flow in ungauged catchments using remote sensing data, the NRCS-CN model, ANN, and the Hydrological Model (HEC-HMS). Their results indicate that both the NRCS-CN and ANN approaches are suitable for predicting river runoff with reasonable accuracy in the investigated sub-catchments, and they found an acceptable correlation between estimated and corrected satellite rainfall. Rahman

et al. (2022) compared machine learning models with the process-based SWAT model for simulating streamflow in the Upper Indus Basin. They found that the machine learning model captured streamflow dynamics and peak flows with exceptionally high accuracy. Shekar et al. (2023) compared the performance of SWAT and artificial intelligence models for monthly rainfall-runoff analysis in the Peddavagu River Basin of India. They found that the artificial intelligence models demonstrated excellent and highly efficient performance in simulating monthly flow. The use of artificial intelligence models is crucial when there is inadequate data for the NRCS-CN method, especially in situations with limited data availability, for runoff prediction (Sivaprakasam et al. 2018).

Conclusions

The main goal of this study was to compare how well two models, one based on data (i.e., data-driven ANN) and the other on concepts (NRCS-CN), predict runoff. A limitation of the NRCS-CN method is that it works best for smaller areas, less than 250 km². When applied to the Koyna River basin, which is much larger (1917 km²), the NRCS-CN method did not perform as well, showing a low predictive performance. Several physical and conceptually based models demand extensive field data, posing challenges in terms of tedious and time-consuming data collection. On the other hand, the data-driven ANN model demonstrated superior performance, even in scenarios with limited data availability. By leveraging historical runoff data and incorporating inputs such as present-day rainfall and antecedent moisture, the ANN model exhibited commendable predictive capabilities, as evidenced by high correlation coefficients (r) and coefficients of determination (R^2). It is essential to recognize that while the ANN model showcased improved predictive performance in this study, the superiority of data-driven models over conceptual ones may vary depending on hydro-climatic conditions and basin characteristics. Therefore, further research is necessary to assess the comparative performance of these models across diverse geographical regions and under varying climatic regimes. Our study highlights the importance of considering the scalability and adaptability of modeling approaches when addressing runoff prediction challenges in large river basins. While the NRCS-CN method remains a valuable tool for smaller catchments, the versatility and robustness of data-driven approaches, exemplified by the ANN model, make them indispensable for addressing the complexities of runoff prediction in larger drainage areas. In conclusion, while acknowledging the strengths and limitations of both

approaches, our findings underscore the efficacy of data-driven artificial intelligence techniques, particularly the ANN model, in enhancing runoff prediction accuracy. By embracing advanced modeling techniques, water resource managers can make more informed decisions, ultimately contributing to more sustainable water resource management practices in river basins worldwide.

Declarations

Conflict of interest The authors declare no competing interests.

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