Prediction of S12-MKII rainfall simulator experimental runoff data sets using hybrid PSR-SVM-FFA approaches

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ABSTRACT

Effective prediction of runoff is a substantial feature for the successful management of hydrological phenomena in arid regions. The present research findings reveal that a rainfall simulator (RS) can be a valuable instrument to estimate runoff as the intensity of rainfall is modifiable in the course of an experimental process, which turns out to be of great advantage. The rainfall-runoff process is a complex physical phenomenon caused by the effect of various parameters. In this research, a new hybrid technique integrating PSR (phase space reconstruction) with FFA (firefly algorithm) and SVM (support vector machine) has gained recognition in various modelling investigations in contrast to the principle of empirical risk minimization through ANN practices. Outcomes of SVM are contrasted against SVM-FFA and PSR-SVM-FFA models. The improvements in NSE (Nash–Sutcliffe efficiency), RMSE (Root Mean Square Error), and WI (Willmott’s Index) by PSR-SVM-FFA over SVM models specify that the prediction accuracy of the hybrid model is better. The established PSR-SVM-FFA model generates preeminent WI values that range from 0.97 to 0.98, while the SVM and SVM-FFA models encompass 0.93–0.95 and 0.96–0.97, respectively. The proposed PSR-SVM-FFA model gives more accurate results and error limiting up to 2–3%.

Key words: PSR-SVM-FFA, rainfall simulator, runoff, SVM, SVM-FFA

HIGHLIGHTS

• The models developed in this study using three algorithms are SVM, SVM-FFA, and hybrid PSR-SVM-FFA models.
• SVM, SVM-FFA, and PSR-SVM-FFA were used, while the earlier studies used simple machine learning approaches for predicting runoff.
• Interactions of all techniques along with five different scenarios are presented.
• Watershed has different slopes; hence, six different types of slope conditions have been considered.

1. INTRODUCTION

The principal purpose of a rainfall simulator (RS) is to simulate natural precipitation precisely and specifically. Simultaneously, RSs regulate the intensity and duration of rainfall. They are beneficial as rainfall can be created swiftly on demand wherever essential, without waiting for natural rainfall at a desired intensity and interval, thus eradicating the unpredictable and erratic unevenness of natural rain (Wildhaber et al. 2012; Iserloh et al. 2013). The necessity for short- and long-term runoff simulation is significant for managing watersheds which comprises surplus runoff control, managing and using runoff for detailed tenacities. The complexity of the rainfall–runoff process and its unpredictability depending on watersheds features and rainfall patterns makes it difficult to predict and estimate with desired accuracy (Abudi et al. 2012; Samantaray et al. 2019, 2021). Yet, hydrologists have recently developed several approaches and models varying from empirical- to physical-based relationships. Physical models have been ascertained to be improved for simulating runoff; however, they require a huge quantity of data. Hence, the necessity to develop alternate models for runoff and sediment yield simulation utilizing accessible data has taken primacy (Samantaray & Sahoo 2020a; Xu et al. 2020; Jimmy et al. 2021; Mohanta et al. 2021). The runoff modelling process is a key constituent in climatological engineering. Therefore, an improved and consistent smart model has to be explored for runoff forecasting that is vital for water resources engineering.

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Pérez-Latorre et al. (2010) developed two diverse RS designs for obtaining rainfall intensities having drop size and energy like that of natural rainfall. Comparing the efficiency of two single simulators, RS-2 gave a more accurate drop-size distribution in the middle part and also a lesser budget than that of RS1. Akbarzadeh et al. (2009) investigated the decline of overland flow and splash detachment of clayey soil after casing it with various synthetic geotextiles utilizing RS as well as neuro-fuzzy and ANN. It was observed that the neuro-fuzzy model gives better estimates followed by ANN and multivariate regression for runoff and splash prediction, respectively. Elhakeem & Papanicolaou (2009) provided comprehensive operational phases for estimating in situ runoff curve number (CN) for certain agronomic fields in Iowa State using RS. Observed results revealed that RSs are valuable devices to estimate in situ runoff CN because the intensity of rainfall was modifiable at the time of an experimental run. Wildhaber et al. (2012) assessed the appropriateness of a new field hybrid RS which combined spray nozzle and dropped former features of RS for soil erosion study and for quantifying the effect of vegetation and soil arrangement permanency on runoff and erosion in sub-alpine parkland region. Outcomes demonstrated that vegetation cover plays a vital part in the soil structure stability of alpine soils. Abudi et al. (2012) designed and tested a movable RS to simulate precipitations that persuade runoff and soil erosion. They observed that the field RS acts as a potent device for field penetration, crusting, and erosion of soil. Iserloh et al. (2013) characterized non-natural rain produced by 13 RSs, constructed in different European research organizations, utilizing Laser Precipitation Monitor and rainfall accumulators in every simulation for ensuring comparability of outcomes. Aksoy et al. (2012) developed a laboratory-gauge non-movable RS to spray rain on a flume which can be provided with both lateral and longitudinal slopes. Performance of RS is assessed based on the intensity of rainfall and its consistency, raindrop size dissemination, and kinetic energy of produced rainfall. Cea et al. (2010) analysed the accuracy and efficiency of 2D vibrant wave models for computing rainfall–runoff directly from rainfall data sets within distinct urban geometries. They also determined different model constraints that are appropriate while using an experimental set-up in a laboratory RS. Fister et al. (2012) evaluated wind and precipitation features of Movable Wind and RS. The adequacy of simulation eminence and condition of suitability for relative measurement of soil erosion in field was assessed. Jin et al. (2009) assessed the impact of residue cover and intensity of rainfall on the runoff loss of soil organic matter directly, by quantifying sediment loss over time and variations in sediments’ particle size distribution, using a field RS in the laboratory.

Sivapragasam et al. (2001) suggested a simple and effective technique based on Singular Spectrum Analysis integrated with SVM for predicting runoff data of the Tryggevaelde catchment, Denmark. Results obtained were contrasted with that of the non-linear prediction (NLP) model and observed that the projected method gives considerably greater accuracy in predicting runoff compared with NLP. Bray & Han (2004) utilized the SVM model, for forecasting flood events, focusing on identifying a suitable model arrangement and its important constraints to model rainfall–runoff process. Behzad et al. (2009) proposed a new machine learning tool called SVM, for runoff modelling of the Bakhtiyari River watershed, Iran. Outcomes of the proposed model were compared with ANN and that of ANN combined with GA and it was observed that SVM performs the best as compared to other models. Okkan & Serbes (2012) examined the applicability of least squares SVM for predicting runoff of the Gordes and Tahtali catchments, located in Turkey, and compared its outcomes with ANN and other regression models. Findings from their study showed that the hybrid model helps in making run time substantially quicker with greater accuracy in runoff prediction. Misra et al. (2009) and Sharma et al. (2015) applied SVM and ANN models for predicting both runoff and sediment concentration of different watersheds. An outcome of SVM was assessed against ANN and simple regression, and it was observed that the SVM model was more competent for predicting runoff and sediment concentration under equivalent prediction accuracy. Jajarmizadeh et al. (2015) compared outcomes of the Soil and Water Assessment Tool (SWAT) with SVM for predicting the monthly streamflow of the Roodan catchment situated in Southern Iran. The SVM model gave better values for average flow as compared with SWAT, while SWAT performed better for predicting entire runoff volume having lesser error during validation. Granata et al. (2016) comparatively studied the modelling of the rainfall–runoff process amid SVM technique and Storm Water Management Model (SWMM) at two gauging stations situated in the northern part of Italy. SVR showed abundant application prospective for applications in the urban hydrologic field as compared to SWMM. Ouyang et al. (2016) applied SVR for forecasting monthly precipitation at a climate station in Changchun, China, and implemented the phase space reconstruction (PSR) method for designing input vectors. Outcomes indicated that the projected amalgam model is reasonable for forecasting monthly precipitation and performs better. Sedighi et al. (2016) studied the performance of ANN and SVM models for simulating the rainfall–runoff process prejudiced by the height of snow water equivalent (SWE) in Roodak catchment, Tehran region, Iran. Contemplation of SWE improves the performance and accuracy of SVM. Wang et al. (2017) projected a novel amalgam model based on variation mode
decomposition, PSR, and wavelet NN augmented by genetic algorithm (GA) to forecast multistep ahead wind speed. Experimental outcomes showed that the projected model outclasses all other models used in the study and performs the best. Sun & Wang (2018) proposed a pioneering amalgam model to forecast wind speed, comprising fast collaborative empirical mode disintegration, model entropy, PSR, and back-propagation NN for enhancing the accuracy of wind speed prediction, and observed that the projected model performed better to forecast short-term wind speed. Lekscha & Donner (2018) compared time interval entrenching and differential entrenching techniques aimed at PSR by examining two fine-premeditated paleo climate sets of data from Ecuador and Mexico. Liu et al. (1998) developed a PSR map from observed streamflow indicators based on the dynamic system concept, for modelling and predicting streamflow on a daily basis. Results revealed that the suggested PSR model could be utilized for making a timid peculiarity amid a noisy and deterministic frenzied indicator. Tao et al. (2018a) projected the hybridization of the SVM model with FFA coupled with PSR for a monthly precipitation forecast in Chhattisgarh, India. The projected model significantly improved the forecasting accuracy of the model and it was found to be a very vigorous smart model, which can be used for the Indian provincial precinct. Mehr et al. (2019) developed a new approach based on the integration of SVR and FFA to forecast monthly precipitation of Tabriz and Urmia substations, Iran. SVR-FFA gives promising accuracy in forecasting precipitation in the semi-arid province as compared to other models. Soleymani et al. (2016) developed an amalgam method comprising Radial Basis Function and FFA for predicting the water level of Selangor River, Malaysia. The performance of RBF-FFA was examined using simulated and real-time water level data and it was found that RBF-FFA is a proficient technique for accurately predicting river water level. Samantaray & Ghose (2020) applied RBFN and BPNN techniques for runoff prediction at the Ong river basin, India. Xu et al. (2020) used FFA with deep learning for improving the prediction efficacy of hydrologic processes, optimizing parameters of SVR spontaneously, and establishing a prediction model for Huangfuchuan in the Fugu region of Shanxi State. Experimental outcomes revealed that the hybrid model accomplished enhanced prediction values. Bozorg-Haddad et al. (2018) implemented GA, SVM, ANN, and dynamic programming for calculating optimal release of hydropower reservoirs of Karoon dam, Iran, under forecasting and non-forecasting scenarios. The SVM model output was compared with other applied models and it was found that SVM and ANN performed best to produce optimal reservoir operation. Tao et al. (2018b) investigated the ability of a hybrid model combining fuzzy model with FA to predict daily reference evapotranspiration over Burkina Faso province. Outcomes showed the effect of using FFA for significantly improving the performance of the conventional ANFIS model.

The objective of this research is to develop a novel hybrid PSR-SVM-FFA model for runoff prediction considering runoff data generated through experimental set-up (RS). The prediction performance of the proposed robust model is assessed against the hybrid SVM-FFA and benchmark SVM model based on different rainfall intensities with respect to basin slope. The application of PSR-SVM-FFA for runoff prediction is a novel approach of the present study.

2. METHODOLOGY

2.1. Support vector machine

SVM is a set of connected supervised learning techniques utilized for classifications and regressions (Vapnik 1998). SVM can be characterized in a double layer network (where given weights are non-linear in principal and linear in the succeeding layer). SVMs choose constraints for the first layer as training input vectors, as this minimizes Vapnik Chervonenkis (VC) dimension. The network structure of SVM is specified in Figure 1.

In mathematical terms, an elementary function for statistical learning procedure is:

$$y = f(x) = \sum_{i=1}^{M} \alpha_i \varphi_i(x) = w \varphi(x)$$ (1)

where output is a linear sum of $M$. Non-linear alteration in Equation (1) is done by $\varphi(x)$. This comprises a big range of models. The decision function of SVM, which is one among the model range, is signified in Equation (2)

$$y = f(x) = \left\{ \sum_{i=1}^{N} \alpha_i K(x_i, x) \right\} - b$$ (2)
where $K$ is the kernel function, $a_i$ and $b$ are constraints obtained by maximizing its objective function, $N$ is the number of training data, $x_i$ are vectors utilized during training, and $x$ is the independent vector.

It utilizes training data to calibrate the model for estimating model constraints, but also retains most vital parts of the input vector in its model (Samantaray & Sahoo 2020b). This vector is known as a support vector. Distinctive structures of kernel functions utilized to transform non-linear input vectors allow SVM to be free from many training vectors, so as to obtain a very small resultant model.

2.2. Firefly algorithm

Yang (2010) introduced a firefly algorithm (FFA) motivated by the societal conduct of fireflies, based on their blinking characteristics. Three important norms in FFA architecture depend on the features of real-world fireflies irrespective of their sex; (i) they are presumed to be unisex, therefore, every firefly can attract another; (ii) luminous intensity regulates the attraction of a single firefly to another; and (iii) flashing intensity is proportionate to the magnitude of light produced by a firefly. On the basis of these norms, the FFA model’s objective function is signified by brightness and light intensity produced from a firefly. Intensity and desirability are given in Equations (3) and (4), respectively. Every firefly has its own desirability $\beta$ with regard to its strength and how it entices other swarm members (Yang 2010).

\[ I = I_0 e^{-\gamma r^2} \]  
\[ w(r) = w_0 e^{-\gamma r^2} \]  

where $w(r)$ and $I$ signify desirability and light intensity at distance $r$ from firefly, in respective order. $w_0$ and $I_0$ are desirability and light intensity at distance $r = 0$ from firefly and $\gamma$ is the coefficient of light immersion. Distance $r_{ij}$ amid any two fireflies $i$ and $j$ is articulated in Equation (5) (Yang 2010):

\[ r_{ij} = \|x_i + x_j\| = \sqrt{\sum_{k=1}^{d}(x_{i,k} - x_{j,k})} \]  

where $x_i$ and $x_j$ are positions of fireflies $i$ and $j$. FFA is modest, supple, and adaptable, which is most effective to solve a varied array of miscellaneous real-world glitches. FFA has the capability to control its modality and control the scale constraint for adapting to a problematic background (Sahoo et al. 2021). For any meta-heuristic algorithm, a moral equilibrium amid utilization and investigation throughout pursuit processes must be sustained for achieving better outcomes. FFA acts as a global method in optimization problems, and hence is designed for exploring search space and probably to give an optimum/near-
optimum result, if utilized solitarily (Fister et al. 2013). The proposed hybrid SVM-FFA model flowchart is presented in Figure 2.

2.3. Phase space reconstruction

The theory of the PSR approach helps in the possible recognition of the chaotic, deterministic, and stochastic nature of dynamic classifications (Sivakumar et al. 2001). PSR is primarily utilized for reconstructing single-variable time series to avoid any univariable in time series. The system's state is signified at each point, while its evolution time is signified at each flight route, corresponding to changing preliminary constraints. Each point or group of points in a system consists of distinctive patterns to attract flight routes toward themselves. This arrangement of pattern designs is identified as attractors.

For estimating the intricacy of attractors in the system, the reconstruction of the phase system is very much needed; hence, attractor behaviour could be defined and enumerated as being multifaceted or not. With assistance of the time delay entrenching concept, a PSR could be fabricated based on univariable dimension time series. PSR of any specified time series can be articulated as follows:

\[ X_t = (X_t, X_{t-1}, X_{t-2}, \ldots, X_{t-(m-1)\tau}), \quad t = 1, 2, \ldots, M; \quad M = n - (m - 1)\tau \]  \hspace{1cm} (6)

where \( t \) is the time delay, \( m \) represents embedding dimensions, while \( M \) signifies the number of points in PSR. PSR amid \( X_t \) and \( X_{t-(m-1)\tau} \), when rebuilt, can graphically depict the existence of an attractor aimed at deterministic chaos in a time series. A phase space sequence of \( m \)-dimensions can be abridged in the subsequent manner (Delafrouz et al. 2017):

\[
\text{PhS} = \begin{bmatrix}
X_1 & X_{1-\tau} & X_{1-2\tau} & X_{1-3\tau} & \ldots & X_{1-(m-1)\tau} \\
\vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\
X_{nm} & X_{nm-\tau} & X_{nm-2\tau} & X_{nm-3\tau} & \ldots & X_{nm-(m-1)\tau}
\end{bmatrix}
\]  \hspace{1cm} (7)

Assortment of an optimum delay time \( t \) along with dimensions of embedding \( m \) is a very significant stage during the construction of a PSR. Mutual information function (MIF) is one of the common methods to determine optimal delay time in context to the scheming of an attractor. An illustration of the hybrid extravagance model is demonstrated in Figure 3.
2.4. Experimental set-up (description of RS)

RS consists of a sand tank that is straddling on a sustenance frame with essential services, features, and arrangements for facilitating studies of groundwater flow, groundwater abstraction, flood hydrographs, and fluvial mechanics. The sump tank and centrifugal pump straddle a casing underneath the sand tank that delivers water for numerous experiments. Water leaving the sand tank from various outlets proceeds to the sump tank under gravitational force for reprocessing (Pérez-Latorre et al. 2010). A centrifugal pump draws water from the sump tank via drumming at the tank bottom. A pressure regulator in every provision ensures that the flow is unaffected by changes in the other feed provided that the regulator is adjusted to suit. The outlet from the centrifugal pump incorporates a pressure relief valve to limit the system pressure to a maximum of approximately 3.0 barg and prevent the pump from overheating, if the flow from the two outlets is restricted or stopped. Water discharging from the relief valve is returned to the sump tank via a connection in the sidewalls of the tank (Elhakeem & Papanicolaou 2009). When demand from the two outlets is high, the relief valve will remain closed to maintain the pressure in the system. When demand is reduced and the system pressure rises above 3.0 barg, the valve will open to relieve the excess flow.

The shallow sand tank is contrived from stainless steel to resist corrosion and should be filled with sand or other granular material as appropriate to the studies. Collection of tapping sockets in the sand tank is linked with multiple tube manometer which permits the determination of water table surface. The level in each tube can be read by sliding the common scale along the track at the top of the manometer. Before using the manometer to measure water levels, it is important to expel air from flexible tubes connecting manometer tubes to tapping points. Each tapping in the sand tank incorporates a filter mesh to retain the sand while allowing the water to flow. Valves and pipework below the sand tank allow water draining from each well to flow back to the sump tank. Supple outlet tubes permit water to be extracted to an accumulating container with the motivation of gauging rates of volumetric flow. The two wells are purposely designed to be short in length so that they can be left in position without affecting the surface flow experiments. The plug of sand directly above each well can be removed if required for abstraction experiments, but the effect on the results will be negligible if the sand is left in place.

Water and sediment exiting the sand tank via the weir chute/diffuser is dropped to the outlet accumulating container that measures water flow and assembles any sediment eroded from the sand chamber. This tank is fabricated from clear acrylic. Rain is delivered to the watershed region by two rows of four sprig spouts overhead the chamber, straddling a sustenance structure. The height of the sprig spouts overhead the sand chamber can be speckled for optimizing experimentation by regulating sustenance structure height. Solitary persons at both ends of the equipment must grip sustenance structure during modification performance. A separating valve upstream of every nozzle permits essential design alteration. Since the flow rate through each nozzle is dependent on the pressure, if the appropriate pressure regulator is adjusted to give the required flow rate, then the flow through each nozzle will remain constant when other nozzles are turned on or off. To achieve this, the feed flow control valve should be opened fully and the pressure regulator adjusted to give the required flow through the nozzles. The flexible tube from the arrangement of spray nozzles is connected to one of the water feeds, when required, using the

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**Figure 3** | Graphical representation of the hybrid PSR-SVM-FFA.
self-sealing quick-release connector. The height of nozzles should be adjusted at a required flow rate to give adequate coverage over the surface of sand without excessive spray over the sides of the sand tank.

River inlet tank straddling on the right side of sand tank permits water stream flowing to the surface of the sand, simulating stream from a watercourse upstream. The river inlet tank is fabricated from stainless steel and is bolted to the end wall of the sand tank adjacent to the shallow cut-out. Water comes in at the tank bottom, courses uphill through a glass marble bed for minimizing any turbulence, and then streams sideward to the sand surface through a rectangular section. An anti-erosion mat is supplied to reduce any local scour where the water enters the sand tank. This mat is buried just beneath the sand surface adjacent to the river inlet tank outlet. The flexible tube from the base of the sand tank is connected to one of the water feeds when required, using the self-sealing quick-release connector.

It has been found through the experimentation that well-graded sand in the range 16/30 mesh (1,000 to 500 μm) will allow all of the experiments described in the teaching manual to be carried out without the need to change the sand between runs. To minimize the cost of filling the tank, using a 16/30 mesh swimming pool silica filter grit is suggested. To fill the tank, 550 kg of sand will be required. Figure 4(b) shows the pictographic view of the RS during the experiment. Statistical parameters of the experimental data set (Burgan & Aksoy 2018) for both training and testing phases are given in Table 1.

2.5. Processing and preparation of data

Runoffs are collected from RS with respect to various rainfall intensities of the pump. To enrich the maximum amount of runoff, first switch on the power supply of the pump, and then switch it off. Data are collected in 5 s intervals up to a constant

Figure 4 | Comprehensible delineation of the PSR-SVM-FFA model. (a) Graphical view of S12-MKII rainfall simulator and (b) pictographic view of watershed during the experiment.
limit of runoff generation. For a period of 1 h, runoff data are taken for model formulation. Data composed from 40 min (480 data) are employed for training and the remaining 20 min (240 data) for the testing model. The following arrangements are applied as input:

| Model  | Input | SVM    | SVM*FFA |
|--------|-------|--------|---------|
| M*1    | P_{t,1} | SVM1   | SVM1*FFA |
| M*2    | P_{t,1}, P_{t,1.5} | SVM2   | SVM2*FFA |
| M*3    | P_{t,1}, P_{t,1.5}, P_{t,2} | SVM3   | SVM3*FFA |
| M*4    | P_{t,1}, P_{t,1.5}, P_{t,2}, P_{t,2.5} | SVM4   | SVM4*FFA |
| M*5    | P_{t,1}, P_{t,1.5}, P_{t,2}, P_{t,2.5}, P_{t,3} | SVM5   | SVM5*FFA |

where $P_{t,1}$ is rainfall when pump input is 1 L/min; $P_{t,1.5}$ is rainfall when pump input is 1.5 L/min; $P_{t,2}$ is rainfall when pump input is 2 L/min; $P_{t,2.5}$ is rainfall when pump input is 2.5 L/min; and $P_{t,3}$ is rainfall when pump input is 3 L/min.

Input and output data before training are put between a quantified range (0–1). This process is identified as normalization. The equation utilized for putting data in the range is

$$Y_i = \frac{Y - Y_{\text{min}}}{Y_{\text{max}} - Y_{\text{min}}}$$  \hspace{1cm} (8)

where $Y_i$ is the converted data set, $Y$ is the actual data set, $Y_{\text{min}}$ is the minimum of actual data set, and $Y_{\text{max}}$ is the maximum of the actual data set.
2.6. Model performance evaluation

Indicators are NSE, RMSE, and WI used to assess the performance of model efficiency. The formulae can be articulated as

\[
\text{NSE} = 1 - \frac{\sum_{i=1}^{N} (A_i - B_i)^2}{\sum_{i=1}^{N} (A_i - \overline{A})^2} - \infty < \text{NS} \leq 1
\]

\[
\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (B_i - A_i)^2}
\]

\[
\text{WI} = 1 - \sqrt{\frac{\sum_{i=1}^{N} (A_i - B_i)^2}{\sum_{i=1}^{N} (|B_i - \overline{A_i}| + |A_i - \overline{A_i}|)^2}}
\]

where \(A_i\) and \(B_i\) are measured and predicted \(i\)th runoffs and \(\overline{A_i}\) is the mean of measured runoffs.

3. RESULTS AND DISCUSSION

3.1. Experimental result

Runoff is generated by using RS for six various slopes (Slope = 0°, Slope = 10°, Slope = 20°, Slope = 30°, Slope = 40°, Slope = 50°) of watersheds in context to different input pump efficiencies (1, 1.5, 2, 2.5, and 3 L/min). As rainfall intensity has an impact on runoff, here a detailed description of runoff for axiom rainfall intensity condition (3 L/min) is given.

When rainfall occurs at maximum intensity in a sloppy horizontal bed modelled with sand, the peak hyetograph is established and achieves the highest flow rate. After achieving the peak steady flow rate with the highest epoch, the rising limb fall and rainfall intensity decrease and reach the minimum flow rate with a step-down decrement of rainfall intensity. Here, the hyetograph achieves the highest flow rate of 0.8 L/min for the 50 slope of the designed bed. Similarly, peak hyetograph is established with the highest flow rate of 0.88 m³/s for 40 slope, 0.78 m³/s for 30, 0.82 m³/s for 20, 0.94 m³/s for 10 slope, and 0.81 m³/s 00 slope.

3.2. Model performance analysis

The performance assessment of various input scenarios utilizing the SVM algorithm is presented in Table 2. Statistical measures like RMSE, WI, and NSE are used for the performance evaluation of models (training and testing phase). Amid five models, SVM5 provides the best performance value for all sloping conditions. While considering the testing period, the best WI values are 0.9412, 0.9344, 0.9378, 0.9516, and 0.9408 for SL-00, SL-10, SL-20, SL-30, and SL-40, respectively. Similarly, preeminent values of WI are 0.9392, 0.9266, 0.9297, 0.9408, 0.9415, and 0.9353 for various slopes in training phases.

Among six slopes, the SVM5-FFA model indicates the best result having a WI value of 0.9543 during training and 0.9716 during the testing phase of SL-40. For rest slopes, the SVM5-FFA model provides the best WI values during both periods among all simulations as presented in Table 3. Model outcomes of SVM-FFA based on NSE, RMSE, and WI for both periods are provided in Table 3.

Results of the PSR-SVM-FFA technique during training and testing periods are given in Table 4. When SL-40 is considered, the obtained WI value shows the best performing results. In SL-40, the best values of WI for training and testing periods are 0.9623 and 0.9812. The WI values for other sloping conditions (SL-00, SL-10, SL-20, SL-30, and SL-50) are presented in Table 4. Based on obtained results, a possible inference regarding the dominance of variables on runoff dynamics can be that dynamics reveal a low-dimension chaotic behaviour, and hence, appropriateness of a low-dimension chaotic method. Manifestation of an ideal embedding dimension, i.e. prediction accuracy increases with an increase in embedding dimension to reach its best, i.e. \(m_{opt} = 14\), and thereafter, reduces with further increase in embedding dimension and best prediction outcomes attained with a small number of neighbours support this argument.
3.3. Assessment of results for applied models

For all slopes, the assessment of the PSR-SVM-FFA model during training and testing periods is represented in Figures 5 and 6. Among all slopes, the best value of WI is obtained in Slope 40. Here, WI values for SVM5, SVM5-FFA, and PSR-SVM-FFA-SL-40 models are 0.9412, 0.9668, and 0.9812, respectively. Hence, it can be observed that prediction models proposed in the present research achieve enhanced prediction performances in comparison to models discussed in the literature. As in the case of any model, runoff predictions provided by a newly applied PSR-SVM-FFA model are related to a certain degree of uncertainty that needs to be enumerated. Uncertainty related to the model structure is assessed for three data-driven models (SVM, SVM-FFA, and PSR-SVM-FFA) considered for best input combination model M#5.

A linear scale plot of actual versus predicted runoff for the proposed model of projected slopes is shown in Figure 7. Results illustrate that estimated peak runoffs are 0.7624, 0.7832, and 0.7903 m³/s for SVM, SVM-FFA, and PSR-SVM-FFA against an actual peak 0.81 m³/s for the slope 0°. The approximated peak runoff is 0.8785, 0.905, and 0.9147 m³/s for SVM, SVM-FFA, and PSR-SVM-FFA adjacent to actual peak 0.94 m³/s for slope 1° condition. Similarly, for slope 2°, tangible runoff is 0.82 m³/s aligned with predicted runoffs 0.7689, 0.7881, and 0.7988 m³/s for SVM, SVM-FFA, and PSR-SVM-FFA, respectively. Correspondingly, apprised peak runoffs are 0.7517, 0.765, and 0.7715 m³/s for SVM, SVM-FFA, and PSR-SVM-FFA against the actual peak 0.79 m³/s for the slope 3°. Similarly, approached peak runoffs are 0.8375, 0.855, and 0.8654 m³/s for SVM, SVM-FFA, and PSR-SVM-FFA adjacent to actual peak 0.88 m³/s for slope 4°. Consistently, for slope 5°, the evaluated peak runoff is 0.79 m³/s associated with predicted runoffs 0.7432, 0.7609, and 0.7705 m³/s for SVM, SVM-FFA, and PSR-SVM-FFA, respectively. Simulations exhibit that the proposed technique can efficiently improve

| Positions | Model | Training | Testing |
|-----------|-------|----------|---------|
|           | NSE   | RMSE     | WI      | NSE   | RMSE     | WI      |
| Slope 0°  | SVM1  | 0.521    | 92.51   | 0.8276 | 0.493    | 90.58   | 0.8462 |
|           | SVM2  | 0.555    | 88.23   | 0.8491 | 0.517    | 85.34   | 0.8697 |
|           | SVM3  | 0.591    | 84.72   | 0.8717 | 0.557    | 81.25   | 0.8956 |
|           | SVM4  | 0.629    | 79.91   | 0.8913 | 0.596    | 77.77   | 0.9233 |
|           | SVM5  | 0.691    | 76.55   | 0.9392 | 0.661    | 73.16   | 0.9412 |
| Slope 1°  | SVM1  | 0.505    | 93.64   | 0.8049 | 0.459    | 91.81   | 0.8326 |
|           | SVM2  | 0.535    | 89.28   | 0.8382 | 0.504    | 87.98   | 0.8618 |
|           | SVM3  | 0.569    | 85.43   | 0.8651 | 0.545    | 83.71   | 0.8891 |
|           | SVM4  | 0.613    | 81.48   | 0.8857 | 0.562    | 78.56   | 0.8995 |
|           | SVM5  | 0.662    | 77.59   | 0.9266 | 0.625    | 73.86   | 0.9344 |
| Slope 2°  | SVM1  | 0.513    | 92.71   | 0.8145 | 0.486    | 90.54   | 0.8401 |
|           | SVM2  | 0.539    | 88.77   | 0.8398 | 0.509    | 86.48   | 0.8654 |
|           | SVM3  | 0.582    | 85.04   | 0.8667 | 0.549    | 82.45   | 0.8909 |
|           | SVM4  | 0.615    | 81.34   | 0.8871 | 0.584    | 78.24   | 0.9144 |
|           | SVM5  | 0.671    | 76.84   | 0.9297 | 0.628    | 75.79   | 0.9378 |
| Slope 3°  | SVM1  | 0.526    | 92.47   | 0.8313 | 0.494    | 89.89   | 0.8541 |
|           | SVM2  | 0.556    | 88.08   | 0.8518 | 0.521    | 84.94   | 0.8719 |
|           | SVM3  | 0.605    | 84.65   | 0.8784 | 0.561    | 80.45   | 0.8947 |
|           | SVM4  | 0.651    | 78.93   | 0.8959 | 0.609    | 75.79   | 0.9256 |
|           | SVM5  | 0.701    | 75.36   | 0.9408 | 0.667    | 69.01   | 0.9516 |
| Slope 4°  | SVM1  | 0.529    | 91.79   | 0.8358 | 0.498    | 88.78   | 0.8581 |
|           | SVM2  | 0.559    | 87.03   | 0.8622 | 0.525    | 84.79   | 0.8739 |
|           | SVM3  | 0.606    | 83.81   | 0.8834 | 0.561    | 80.38   | 0.8966 |
|           | SVM4  | 0.656    | 78.89   | 0.8991 | 0.621    | 75.77   | 0.9272 |
|           | SVM5  | 0.704    | 73.58   | 0.9415 | 0.669    | 69.59   | 0.9518 |
| Slope 5°  | SVM1  | 0.518    | 92.61   | 0.8179 | 0.492    | 90.41   | 0.8415 |
|           | SVM2  | 0.544    | 88.37   | 0.8443 | 0.515    | 85.87   | 0.8668 |
|           | SVM3  | 0.591    | 84.79   | 0.8717 | 0.549    | 81.65   | 0.8915 |
|           | SVM4  | 0.619    | 81.32   | 0.8902 | 0.592    | 78.12   | 0.9162 |
|           | SVM5  | 0.689    | 76.69   | 0.9333 | 0.656    | 73.27   | 0.9408 |
the forecasting accurateness of many conventional techniques in terms of all applied evaluation indices. Therefore, a robust
data-driven model with powerful performances is proposed for forecasting experimental runoff.

The box plot of actual and estimated runoff values was drawn as presented in Figure 8. It can be observed that data ranges,
quantiles, and medians for predicted runoff values were analogous to those of actual runoff values. Interquartile ranges of all
models show similarity with actual runoff. In the present study, outliers were not mentioned in Figure 8. They signify an
extreme runoff value (maximum and minimum peak) – that is, runoff in the course of high flow and low flow periods.

### Table 3 | SVM-FFA model results

| Positions | Model | Training period | Testing period |
|-----------|-------|----------------|----------------|
|           |       | NSE | RMSE | WI | NSE | RMSE | WI |
| Slope 0°  | SVM°FKA | 0.696 | 90.24 | 0.8442 | 0.664 | 88.67 | 0.8521 |
|           | SVMI°FKA | 0.719 | 86.01 | 0.8698 | 0.694 | 83.82 | 0.8777 |
|           | SVMII°FKA | 0.754 | 82.45 | 0.9084 | 0.729 | 78.91 | 0.9193 |
|           | SVMIII°FKA | 0.789 | 77.77 | 0.9378 | 0.755 | 75.52 | 0.9482 |
|           | SVMIV°FKA | 0.821 | 73.81 | 0.9487 | 0.791 | 69.75 | 0.9668 |
| Slope 1°  | SVM°FKA | 0.687 | 91.69 | 0.8273 | 0.656 | 90.41 | 0.8349 |
|           | SVMI°FKA | 0.702 | 87.82 | 0.8574 | 0.677 | 86.14 | 0.8703 |
|           | SVMII°FKA | 0.745 | 83.72 | 0.8946 | 0.713 | 80.77 | 0.9085 |
|           | SVMIII°FKA | 0.777 | 79.33 | 0.9329 | 0.741 | 76.53 | 0.9444 |
|           | SVMIV°FKA | 0.802 | 74.22 | 0.9473 | 0.766 | 70.58 | 0.9606 |
| Slope 2°  | SVM°FKA | 0.689 | 91.55 | 0.8313 | 0.657 | 89.14 | 0.8453 |
|           | SVMI°FKA | 0.705 | 87.64 | 0.8672 | 0.681 | 84.82 | 0.8736 |
|           | SVMII°FKA | 0.751 | 83.54 | 0.8975 | 0.718 | 80.66 | 0.9111 |
|           | SVMIII°FKA | 0.781 | 78.03 | 0.9338 | 0.744 | 75.79 | 0.9468 |
|           | SVMIV°FKA | 0.808 | 74.14 | 0.9474 | 0.768 | 68.73 | 0.9684 |
| Slope 3°  | SVM°FKA | 0.699 | 88.89 | 0.8537 | 0.671 | 86.51 | 0.8652 |
|           | SVMI°FKA | 0.722 | 85.89 | 0.8714 | 0.697 | 83.67 | 0.8793 |
|           | SVMII°FKA | 0.761 | 80.89 | 0.9162 | 0.731 | 78.64 | 0.9227 |
|           | SVMIII°FKA | 0.791 | 76.68 | 0.9418 | 0.759 | 73.54 | 0.9493 |
|           | SVMIV°FKA | 0.823 | 70.41 | 0.9491 | 0.799 | 68.35 | 0.9684 |
| Slope 4°  | SVM°FKA | 0.701 | 89.57 | 0.8553 | 0.674 | 86.34 | 0.8681 |
|           | SVMI°FKA | 0.725 | 85.55 | 0.8786 | 0.706 | 82.57 | 0.8947 |
|           | SVMII°FKA | 0.767 | 80.41 | 0.9231 | 0.734 | 78.49 | 0.9382 |
|           | SVMIII°FKA | 0.798 | 76.54 | 0.9489 | 0.762 | 73.35 | 0.9554 |
|           | SVMIV°FKA | 0.851 | 70.23 | 0.9543 | 0.802 | 67.74 | 0.9716 |
| Slope 5°  | SVM°FKA | 0.693 | 90.42 | 0.8343 | 0.662 | 88.87 | 0.8482 |
|           | SVMI°FKA | 0.716 | 86.67 | 0.8682 | 0.688 | 84.21 | 0.8757 |
|           | SVMII°FKA | 0.753 | 83.39 | 0.9016 | 0.724 | 79.02 | 0.9123 |
|           | SVMIII°FKA | 0.783 | 77.78 | 0.9352 | 0.751 | 75.62 | 0.9478 |
|           | SVMIV°FKA | 0.815 | 73.95 | 0.9477 | 0.787 | 69.93 | 0.9632 |

### Table 4 | Values of τ, m with results of PSR-SVM-FFA model

| Model | Optimal parameters of τ, m for PSR | Training period | Testing period |
|-------|-----------------------------------|----------------|----------------|
|       |                                   | NSE | RMSE | WI | NSE | RMSE | WI |
| PSR-SVM-FFA-SL-0°  | (m = 14, τ = 5) | 0.926 | 52.89 | 0.9565 | 0.878 | 60.38 | 0.9757 |
| PSR-SVM-FFA-SL-1°  | (m = 14, τ = 5) | 0.883 | 59.34 | 0.9546 | 0.836 | 63.21 | 0.9731 |
| PSR-SVM-FFA-SL-2°  | (m = 14, τ = 5) | 0.899 | 57.09 | 0.9555 | 0.854 | 62.49 | 0.9742 |
| PSR-SVM-FFA-SL-3°  | (m = 14, τ = 5) | 0.943 | 49.77 | 0.9584 | 0.889 | 59.23 | 0.9767 |
| PSR-SVM-FFA-SL-4°  | (m = 14, τ = 5) | 0.958 | 45.01 | 0.9623 | 0.904 | 55.56 | 0.9812 |
| PSR-SVM-FFA-SL-5°  | (m = 14, τ = 5) | 0.901 | 55.13 | 0.9556 | 0.865 | 61.65 | 0.9751 |
PSR-SVM-FFA performed better in apprehending extreme runoff, while SVM and SVM-FFA could not capture either top, bottom, or both extremes. The reason is that SVM and SVM-FFA techniques applied in the present study had a comparatively less complex structure and fewer operational parameters than the PSR-SVM-FFA model.

Figure 5 | Actual versus predicted runoff for (a) Slope 0°, (b) Slope 1°, (c) Slope 2°, (d) Slope 3°, (e) Slope 4°, and (f) Slope 5° during training phase.
Figure 6 | Actual versus predicted runoff for (a) Slope 0°, (b) Slope 1°, (c) Slope 2°, (d) Slope 3°, (e) Slope 4°, and (f) Slope 5° during testing phase.
Figure 7 | Deviation of actual and predicted runoff at (a) Slope 0°, (b) Slope 1°, (c) Slope 2°, (d) Slope 3°, (e) Slope 4°, and (f) Slope 5° condition during testing phase. (continued.)
To have better knowledge with regard to the prediction accuracy of three challenging techniques, SVM, SVM-FFA, and PSR-SVM-FFA, a comparison is done between runoff values of varied observations, ranges, and predictions. Histogram plots of observed and estimated runoff values are demonstrated in Figure 9. Plots in Figure 9 signify the occurrence
Figure 7 | Continued.
Figure 7 | Continued.
Figure 7 | Continued.
Figure 7 | Continued.
Figure 8 | Box plots of runoff estimates of various ML models and observed runoff. (continued.)
Figure 8 | Continued.
probability of runoff between a precise range. The estimation of runoff for all slope conditions shows that for the lowest (0.0–0.1 m$^3$/s) and the highest (0.7–0.8 m$^3$/s) ranges of runoff. The frequency (number of events) of precise estimations by the PSR-SVM-FFA model illustrates improved agreement with the frequency of observed values than that of the frequency of precise estimations by the SVM-FFA and stand-alone SVM model.

### 3.4. Assessment of various models

Statistical indicators like NSE, RMSE, and WI are used to evaluate the performance of SVM, SVM-FFA, and PSR-SVM-FFA models for various slope conditions. The assessment of performance measures is indicated in Table 5, which shows the effectiveness of each model. Runoff evaluation is significant, and hence, methods applied here are important to demonstrate runoff information. It is evident that PSR-SVM-FFA performs the best when compared with SVM-FFA and SVM. The assessment of each model is demonstrated in Figure 10 in terms of linear bar scheme. These experimental results revealed that the PSR-SVM-FFA model obtained more reliable prediction runoff values and had a clear advantage over other proposed models in runoff prediction. Hence, the proposed PSR-SVM-FFA is fit for the prediction intervals of a certain period in the runoff series and provides supporting information for decision-makers in water resources management.

![Figure 9](http://iwaponline.com/jwcc/article-pdf/13/2/707/1013564/jwc0130707.pdf)

*Figure 9* | Histogram plot of actual versus SVM, SVM-FFA, and PSR-SVM-FFA for (a) Slope 0$^\circ$, (b) Slope 1$^\circ$, (c) Slope 2$^\circ$, (d) Slope 3$^\circ$, (e) Slope 4$^\circ$, and (f) Slope 5$^\circ$ condition. (continued.)
for wide-spread good performance to predict runoff in similar conditions. Also, the present research findings can be used for irrigation and water resources engineering to design a hydraulics structure for agriculture. Basically, this study will be helpful where runoff measurement is impossible or simply for un-gauged catchments. In that situation, if a researcher/scientist knows the watershed/region slope, rainfall amount, and type of soil available there, then, with the help of RS, runoff data are generated, which will be helpful for runoff prediction. In reference to the objective of the present study (which is to present a newly developed method of runoff prediction), it is indicated that at least one case study is needed to verify the applicability of the presented model, and hence, others might apply for other scenarios. Similarly, the proposed approach can be applied to two or more different case studies for observing the validity and performance of models under different circumstances.

The advantages of proposed data-driven models are that all models attained suitable simulation outcomes; yet, their modelling complexities and costs vary. Conventional models necessitate a huge volume of input data; hence, data pre-processing, distribution, and validation processes are restricted by unsolved data assortment. In addition, conventional models utilize formulae for imitating certainty; however, imitation can never precisely match certainty. In general, simplification of real-world presents ambiguity and drops the accuracy of results. Artificial intelligence models have flexible model architectures and controlling input data parameters, which accelerate modelling procedures by reducing modelling uncertainty. Hybrid data-driven models also attained better performances, with much simpler procedures and at a lower cost. In brief, the PSR-SVM-FFA

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**Figure 9** | Continued.
model is simpler and more appropriate. Previous studies have all emphasized the high efficiency and accuracy of the various hybrid models (Van et al. 2020; Han & Morrison 2021; Ouma et al. 2021; Reddy et al. 2021) in runoff prediction. In the current study, it was shown that the proposed PSR-SVM-FFA approach found more efficacy and superiority.

### Table 5 | Performance index of various approaches for runoff prediction

| Watershed bed slope | SVM  | SVM-FFA | PSR-SVM-FFA |
|---------------------|------|---------|-------------|
| Slope 0°            | NSE  | RMSE    | WI          |
|                     | 0.661| 73.16   | 0.9412      |
| Slope 1°            | 0.625| 73.86   | 0.9344      |
| Slope 2°            | 0.628| 73.79   | 0.9378      |
| Slope 3°            | 0.667| 69.01   | 0.9516      |
| Slope 4°            | 0.669| 69.59   | 0.9518      |
| Slope 5°            | 0.656| 73.27   | 0.9408      |

Figure 9 | Continued.
Figure 10 | Comparison of the performance index for the proposed watershed (a) training and (b) testing phases.
One limitation of this study is the consideration of experimental set-up within the laboratory room (i.e. at constant room temperature). Future research will include testing of the proposed approach on field study (River gauge station). Also, emphasis should be given to evaluating the usage of additional input variables for hydrological predictions produced from weather data (collected climatological data) utilizing sediment load, groundwater level, and flood modeling, as an alternative prediction performance. Additionally, satellite data can be assimilated as an external instructive characteristic to the prediction matrix where more precise prediction accuracy can be attained.

4. CONCLUSION
The major benefit of an RS is its compressed structure which fits well in a laboratory room for constructing the economic model. In the present study, the potential of the PSR-SVM-FFA model is compared with the SVM-FFA and standard SVM model for runoff prediction, considering distinguished experimental runoff data emerged from RS. Results obtained from this study specify that the PSR-SVM-FFA method is helpful for modelling rainfall–runoff series that consist of six different slopes of watershed, which gives good prediction performance compared to other proposed models. Outcomes of various performance indices demonstrate that PSR-SVM-FFA has a better ability for non-linear complex mapping. The results indicate a minimal change in the amount of predicted runoff volume and peaks, at different rainfall intensities. This study recommends that the proposed hybrid method can be adopted for modelling other hydrological parameters. Also, this study can be a basis for future studies in different parametric conditions like infiltration and evapotranspiration losses. Application of other robust data-driven models seeking runoff prediction can also be considered for further analysis.

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The authors declare that they have no conflict of interest.

CONSENT TO PARTICIPATE
The authors have made a significant contribution to this manuscript, have seen, and approved the final manuscript.

AUTHORS’ CONTRIBUTIONS
S. S.: Conceptualization, Roles/Writing – original draft, Methodology, Formal analysis, Experiment, Data curation, Formal analysis, Writing – review and editing. D. K. G.: Visualization, Project administration.

DATA AVAILABILITY STATEMENT
Data cannot be made publicly available; readers should contact the corresponding author for details.

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