Rainfall-runoff modelling using soft computing techniques for various watersheds of Madhya Pradesh, India

SEEMA KUSHWAHA* and PRAVENDRA KUMAR

Department of Soil and Water Conservation Engineering, College of Technology, G.B. Pant University of Agriculture and Technology, Pantnagar (U.S. Nagar, Uttarakhand)
**Corresponding author's email id: seemrajsan@gmail.com*

ABSTRACT: The main study was the estimation of runoff using present day and previous days rainfall and previous days runoff as a daily input variable using artificial neural networks (ANNs) and wavelet-based ANNs (WANNs). Rainfall-runoff data were collected, standardized, and selected as inputs using the Gamma test. The methodology for runoff estimation and modeling using ANNs and WANNs was applied to the regions of Narsimhpur and Mandla in Madhya Pradesh. As the number of neurons was increased, the correlation between rainfall and runoff was initially improved and then reduced. Therefore, an optimum number of neurons was identified at which the best correlation was achieved. Better correlation coefficients, least root mean square errors, higher Nash-Sutcliffe efficiency, and greater Willmott indices were obtained for WANNs models compared to ANNs models. These results can be utilized for runoff forecasting.

Keywords: Artificial Neural Networks (ANNs), Nash Shutcliff coefficient of efficiency, Wavelet

Water is considered the main component of elements for living beings. It is acknowledged as a major component of the hydrosphere. The hydrosphere is defined in terms of the occurrence, circulation, and distribution of water. The processes through which water is vaporized from surface sources and living organisms are known as evaporation and transpiration. After vaporization, water is condensed into the atmosphere and circulated in the form of clouds, leading to precipitation or rainfall.

Latterly, significant focus has been directed toward the study of runoff and its spatial and temporal variations. An urgency has been recognized for the development of an effective soil and water management system to address challenges posed by water scarcity and natural disasters such as floods and landslides. Rainfall–runoff modeling has been recognized as a suitable tool for runoff prediction, enabling the implementation of protective actions anti phenomena like floods (Singh *et al*., 2022).

In recent decades, the accurate modeling of runoff has been actively pursued by researchers in hydrology due to its significance in water resource planning, water power generation, urban planning, irrigation, and other meteorological applications. Vast datasets and complex environmental computations have been required by conceptual and physical models. Because of the nonlinear nature of the rainfall–runoff process and the complexity of physical models, intelligent models have been employed. However, inconsistent or illogical results have occasionally been generated when nonlinear hydrological systems were modeled.

Notably, nonlinear artificial neural networks (ANNs) have been utilized for the successful prediction of hydrological time series (Mirzania *et al*., 2021). To simulate river flow from catchments, atmospheric, dynamic, and static models are incorporated within hydrological modeling frameworks. The precision of hydrologic modeling is vastly concerned by the characteristic of data. Therefore, difficulties are encountered in model simulation when data availability is limited. Physical flow measurements are considered infeasible within the spatiotemporal domain, and in such cases, river flow simulation is supported through soft computing techniques (Rathnayake *et al*., 2023). Runoff is recognized foremost complex and critical phenomena in the hydrological cycle. For its modeling, multiple perspectives have been introduced to enhance the development and refinement of predictive models. Cognitive computing has been engaged to reliably model hydrological processes (Saravani *et al*., 2023).

Rainfall-runoff modeling has been enhanced to improve streamflow prediction through the use of more accurate data and modeling techniques, which are deliberated indispensable for effective water control and overflow risk mitigation. Rainfall-runoff modeling has been computed using machine learning and conceptual models (Daif *et al*., 2025). Coordinated water resource planning has been defined as a process in which water, land, and associated resources are developed and managed equitably without compromising sustainability. Computational tools ranging from simple lumped models to complex distributed watershed models have been introduced, and soft computing and inferential methods have been implemented to address water resource challenges. Composite models have been perceived to perform superiority in various studies. However, variation in prediction accuracy and uncertainty has been reported across models. A universally best-performing model has not been recognized, as effectiveness is determined by the characteristics of the data applied (Rosamma, 2022).

Floods have been categorized among the most destructive natural disasters, and modeling complexities have been encountered. Flood anticipatory models have been evolved to reduce risk, provide policy insights, minimize human loss, and mitigate property damage. Over the past two decades, key input has been created by machine learning methods to replicate the complex physical processes of floods mathematically, offering enhanced performance and cost-efficient solutions. The growing popularity of machine learning among hydrologists has been attributed to its vast benefits and applications. More accurate and efficient models have been pursued through the proposal of novel machine learning methods and the hybridization of existing ones. Key trends such as hybridization, data decomposition, algorithm ensembles, and model optimization have been reported as influential in improving flood prediction models. This reconsideration has been perspective as a guideline for hydrologists and climate scientists in selecting suitable machine learning methods aligned with the prediction task (Mosavi *et al*., 2018). Within catchments, significant impacts on land productivity have been perceived due to changes in streamflow, which affect soil moisture retention and nutrient availability through usually desiccating and rinsing cycles. To anticipate prospective adapt and delve into the influence of different eventuality, cognitive computing have been employed lately in the water field for streamflow simulation (Gharbia *et al*., 2022). Severe and devastating consequences are caused by flooding across the globe; an increase in the frequency and severity of these events is expected due to climate change. Advances in flood modeling and prediction methods, along with developments in open-source data and computing capabilities, have made flood modeling methods more accessible. However, a challenge is posed by the diversity in modeling approaches and available data sources when determining approach the most suited to a study area (Ramsamy, 2022).

MATERIALS AND METHODS

Narsimhpur has been identified as a watershed through which the Narmada River flows across Madhya Pradesh. This watershed is located between 22°54′59.99″N latitude and 79°09′60.00″E longitude. The Narmada River is believed to originate from the Amarkantak Plateau in the Anuppur district of Madhya Pradesh. A total length of 1,312 kilometers has been attributed to the Narmada River. In the region traversed by the river, the catchment area of the Narsimhpur watershed has been measured at 5,125.55 square kilometers. An elevation of 347 meters (1,138 feet) prior datum has been recorded for the watershed. Warm season temperatures have been noticed to range from 45°C to 46°C, while during colder periods, temperatures drop to approximately 9°C. The rainy season in this watershed is noted to occur from June to September. During the monsoon, an average rainfall of 40 inches is received. The culturable command area (CCA) of this catchment area has been described to be 131,925 hectares. Mandla is situated between 22°36′0.00″N latitude and 80°22′48.00″E longitude. The watershed area has been measured at 8,771 square kilometers. An elevation of 539 meters (1,768 feet) prior datum has been registered. During summer, temperatures are observed to range from 25°C to 45°C. The rainy season in Mandla is understood to begin in June and continue through September. In winter, temperatures are found to range from 11°C to 21°C. An average annual rainfall of 1,427.7 millimeters has been reported. The culturable command area of Mandla has been estimated at 14,000 hectares.

To achieve optimum and efficient training between input and output data, all data were systematized using a standard normal variable (z). Simple and rapid training convergence within a narrow range was enabled during model development. Dimensionality was eliminated, allowing equal weightage to be assigned to all variables. The standard normal variable has been defined as:

$Z = (x - \mu)/\sigma$…(1)

Where, μ is mean of the observed variable and σ is standard deviation of observed variable.

Wavelets used in continuous wavelet transforms (CWTs) are governed by the uncertainty principle derived from Fourier analysis and sampling theory: the simultaneous precise assignment of time and frequency to a signal event is not permitted. A lower bound is possessed by the uncertainty product of time and frequency. Consequently, events are represented as entire regions in the time-scale plane in a scaleogram, rather than as singular points. Discrete wavelet bases are also interpreted in accordance with other uncertainty principles.

The discrete wavelet transform has been acknowledged for operating with reduced computational complexity, requiring only O(N) time, in contrast to the O(N log N) time required by the fast Fourier transform (FFT). This advantage is attributed not to the transform itself, but to the use of logarithmic frequency division—unlike the FFT, which is founded on evenly spaced frequency divisions using discrete Fourier transform (DFT) basis functions.

This complexity consideration is applicable only when the filter size is not directly associated the signal size. A wavelet lacking compact support, including the Shannon wavelet, would necessitate $O(N^2)$ operations. It is worth mentioning a logarithmic Fourier Transform is also available with O(N) complexity, although logarithmic sampling in time is required—making it suitable only for specific signal types.

Data compression is typically carried out using an approximation to the Discrete Wavelet Transform (DWT), assuming prior signal sampling. Signal analysis is commonly conducted using the CWT. The DWT approximation is employed in engineering and computer science, while the CWT is utilized in scientific research. Data transformation and encoding have been accomplished through wavelet transforms, enabling efficient compression.

RESULTS AND DISCUSSION

A total of 14 model provided were developed with varying hidden layer size to examine the impact of attribute of input variability on model performance. The optimal numerous sensory neurons in the hidden layer were also investigated, ranging from 3 to 42—for example, 6-3-3-1, 6-6-6-1, 6-9-9-1, 6-12-12-1 up to 6-42-42-1. These configurations represent single-layered neural network and a pair of hidden layers neuron counts. The neuronal density in the hidden layers was increased in intervals of 3 (from 3 to 42), while the input layer maintained a constant 6 neurons. The maximum permitted number of neurons was reached for each of the 14 models. For runoff estimation using the ANN model, each model was operated by dissevering the input and output data into 70% for training and 30% for testing. The runoff function is defined by Equation (2) using rainfall and runoff from previous days. Based on the findings Gamma test, the input combination consists of present-day rainfall, previous one-day rainfall, and runoff from the previous three days.

$Q_t = f(R_t, R_{t-1}, R_{t-2}, R_{t-3}, Q_{t-1}, Q_{t-2})$…(2)

Artificial neural network models for Narsimhpur

The best models for training and testing are shown in Table 4.4. After best practice anaysis the prediction performance of all models, it can be displayed that ANN-6 having architecture (6-18-18-1) showed the enhanced performance during training having minimum value of RMSE (0.9061 cumec), maximum value of correlation coefficient (r = 0.82), maximum value of NSCE (0.90), PARE divergent from $-0.9*10^{-3}$, upmost value of WI (0.80) and MAE varied from 1.1. The values for training and testing of RMSE, correlation coefficient, NSCE, PARE, WI and MAE varied from 0.9061 cumec to 1.104 cumec., 0.82 to 0.90, 0.90 to 0.70, $-0.9*10^{-3}$ to $-0.42*10^{-3}$, 0.80 to 0.82 and 1.1 to 1.1 respectively. Negative value of PARE showed under-anticipated and positive value of PARE showed over-anticipated. ANN-06 with architecture (6-36-36-1) showed minimum PARE value of -0.42*10^{-3}. Fig. 4.1 showed an under-predicted model for testing as observed and predicted runoff values represented to be in close agreement.

ANN model for Mandla

The best models for training and testing are shown in Table 4.6. After best practice anaysis prediction performance of all models, it can be revealed that ANN-06 having architecture (6-18-18-1) showed the enhanced performance of all during training having minimum value of RMSE (0.849 cumec), supreme value of correlation coefficient (r = 0.80), uttermost value of NSCE (0.67), PARE value of -0.9*10^{-3}, upmost value of WI (0.72) and MAE value of 1.2. The values of RMSE, correlation coefficient, NSCE, WI, PARE and MAE varied from 0.849 cumec to 0.849 cumec., 0.80 to 0.89, 0.67 to 0.83, 0.72 to 0.80, -0.9*10^{-3} to -1.2*10^{-3} and 1.2 to 1.2, respectively. Fig 1 showed an under-anticipated model for training and testing as observed and anticipated runoff values represented to be in close agreement.

Wavelet neural network based runoff prediction models for Narsimhpur

The results of computational assessment for training and testing are presented in Table 3. The Table 3 shows the values of unparallel performance indicators for training and testing data which were used for nomination of the best runoff anticipated model. It can be observed for training data values of RMSE, correlation coefficient, NSCE, WI, MAE and PARE ranged from 0.651, 0.93, 0.89, 0.80, 2.1 and 0.80*10^{-3} . It can be deduced that model WANN-06 having architecture (6-18-18-1) showed the best performance having minimum value of RMSE (0.651 cumec), maximum value of correlation coefficient (0.93), maximum value of NSCE (0.89), maximum value of WI (0.80), minimum value of MAE (2.1) and minimum PARE value of 0.80*10^{-3}. For testing data, model 6 given best values of RMSE, correlation coefficient, NSCE, WI, MAE and PARE varied from 0.9061, 0.84, 0.73, 0.73, 2.1 and -1.5*10^{-3}.

Table 1: Key performance indicators for ANN (training and testing) based runoff prediction models of Narsimhpur

Model	Architecture	Training RMSE (cumec)	r	NSCE	PARE (10^{-3})	WI	MAE	Testing RMSE (cumec)	r	NSCE	PARE (10^{-3})	WI	MAE
ANN-01	6-3-3-1	1.0190	0.78	0.80	-3.2	0.70	4.1	1.1327	0.80	0.60	-1.2	0.80	5.1
ANN-02	6-6-6-1	0.9300	0.76	0.82	-3.3	0.72	4.5	1.1607	0.82	0.63	-2.1	0.81	5.2
ANN-03	6-9-9-1	0.9900	0.77	0.83	-3.1	0.73	4.3	1.218	0.83	0.64	-2.3	0.83	5.3
ANN-04	6-12-12-1	0.9300	0.78	0.88	-3.0	0.74	4.6	1.246	0.88	0.67	-2.4	0.82	5.4
ANN-05	6-15-15-1	1.0190	0.73	0.85	-2.5	0.75	3.2	1.274	0.85	0.78	-2.5	0.88	5.6
ANN-06	6-18-18-1	0.9061	0.82	0.90	-0.9	0.80	1.1	1.104	0.90	0.70	-0.42	0.82	1.1
ANN-07	6-21-21-1	1.1327	0.75	0.86	-1.2	0.79	2.1	1.1327	0.86	0.72	-0.56	0.80	1.2
ANN-08	6-24-24-1	1.1609	0.77	0.87	-1.3	0.77	2.3	1.1609	0.87	0.77	0.28	0.79	1.3
ANN-09	6-27-27-1	1.2740	0.80	0.88	-1.1	0.78	2.4	1.189	0.88	0.76	-2.1	0.77	1.4
ANN-10	6-30-30-1	1.2460	0.72	0.86	-1.2	0.76	2.5	1.218	0.86	0.72	-2.2	0.76	3.1
ANN-11	6-33-33-1	1.2180	0.73	0.85	0.80	0.74	2.6	1.246	0.85	0.71	-2.3	0.77	3.2
ANN-12	6-36-36-1	1.1890	0.70	0.88	0.56	0.75	3.2	1.189	0.88	0.68	-3.1	0.80	2.5
ANN-13	6-39-39-1	1.1327	0.73	0.82	-1.2	0.72	3.3	1.1609	0.82	0.69	-3.2	0.81	3.6
ANN-14	6-42-42-1	1.1607	0.76	0.81	-3.2	0.75	3.4	1.1327	0.81	0.67	-4.1	0,77	4.1

Table 2: Key different performance indicators for ANN (training and testing) based runoff prediction models of Mandla

Model	Architecture	Training RMSE (cumec)	r	NSCE	PARE (10^{-3})	WI	MAE	Testing RMSE (cumec)	r	NSCE	PARE (10^{-3})	WI	MAE
ANN-01	6-3-3-1	1.019	0.70	0.62	-2.1	0.60	2.1	1.1327	0.80	0.80	-4.2	0.70	2.1
ANN-02	6-6-6-1	1.048	0.72	0.63	-2.3	0.62	2.3	1.1609	0.81	0.82	-4.3	0.71	2.5
ANN-03	6-9-9-1	1.076	0.73	0.64	-3.1	0.63	2.5	1.189	0.82	0.80	-2.2	0.72	2.6
ANN-04	6-12-12-1	0.963	0.74	0.65	-3.2	0.64	2.6	1.218	0.83	0.81	-2.3	0.73	2.7
ANN-05	6-15-15-1	0.990	0.75	0.66	-3.3	0.65	2.7	1.246	0.84	0.82	-2.4	0.74	2.3
ANN-06	6-18-18-1	0.849	0.80	0.67	-0.9	0.72	1.2	0.849	0.89	0.83	-1.2	0.80	1.2
ANN-07	6-21-21-1	0.906	0.79	0.60	-2.5	0.69	2.3	0.9061	0.86	0.78	-1.3	0.79	1.3
ANN-08	6-24-24-1	0.877	0.78	0.58	-2.6	0.62	3.1	0.877	0.85	0.77	0.56	0.78	1.5
ANN-09	6-27-27-1	0.930	0.77	0.52	-2.7	0.63	3.2	0.963	0.84	0.73	0.28	0.77	1.3
ANN-10	6-30-30-1	0.963	0.76	0.55	0.50	0.65	3.3	0.99	0.86	0.77	0.26	0.75	4.1
ANN-11	6-33-33-1	0.990	0.73	0.53	0.28	0.64	4.1	1.019	0.77	0.79	0.90	0.76	4.2
ANN-12	6-36-36-1	1.019	0.72	0.60	0.82	0.62	4.8	1.048	0.78	0.77	-3.1	0.74	4.3
ANN-13	6-39-39-1	1.076	0.71	0.61	0.86	0.65	4.9	1.076	0.75	0.76	-3.2	0.73	2.3
ANN-14	6-42-42-1	1.104	0.70	0.63	-1.2	0.62	4.2	1.104	0.72	0.75	-4.2	0.75	2.2

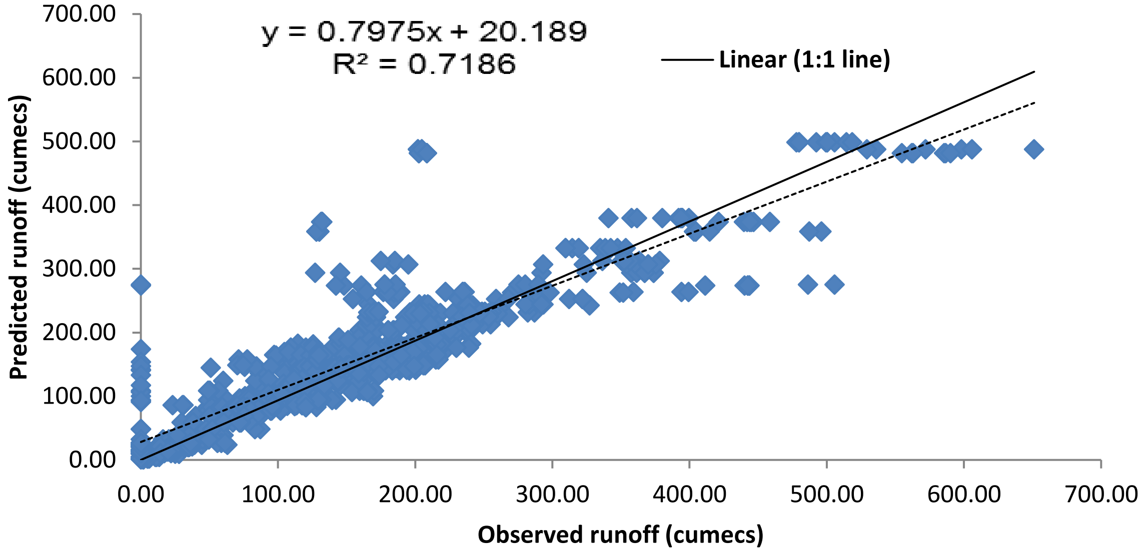

Fig. 1: Scatter plot of predicted and observed runoff for ANN-06 (6-18-18-1) model during training period for Narsimhpur

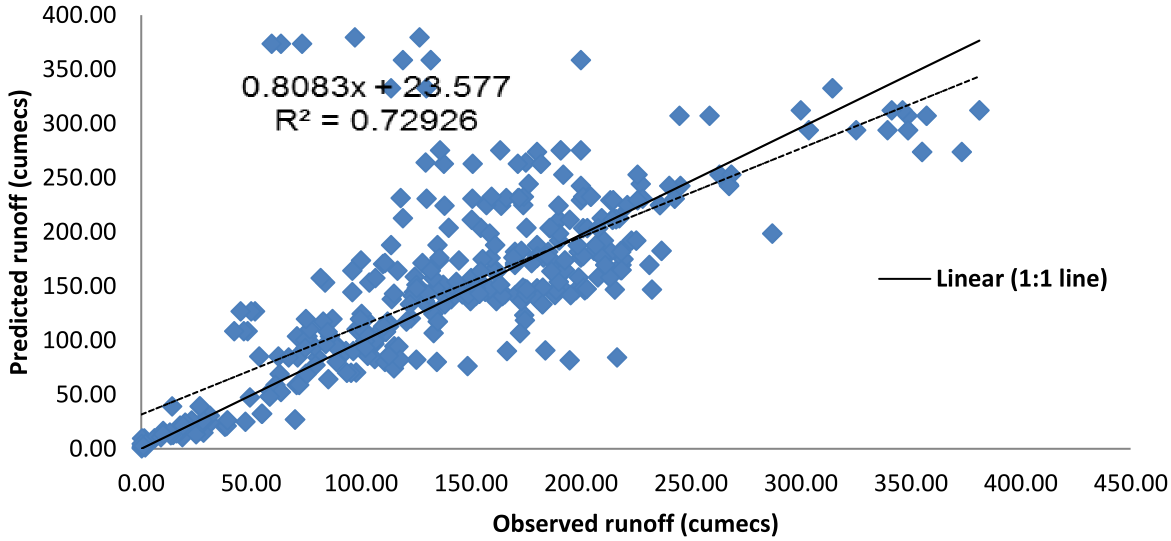

Fig. 2: Scatter plot of predicted and observed runoff for ANN-06 (6-18-18-1) model during testing period for Narsimhpur

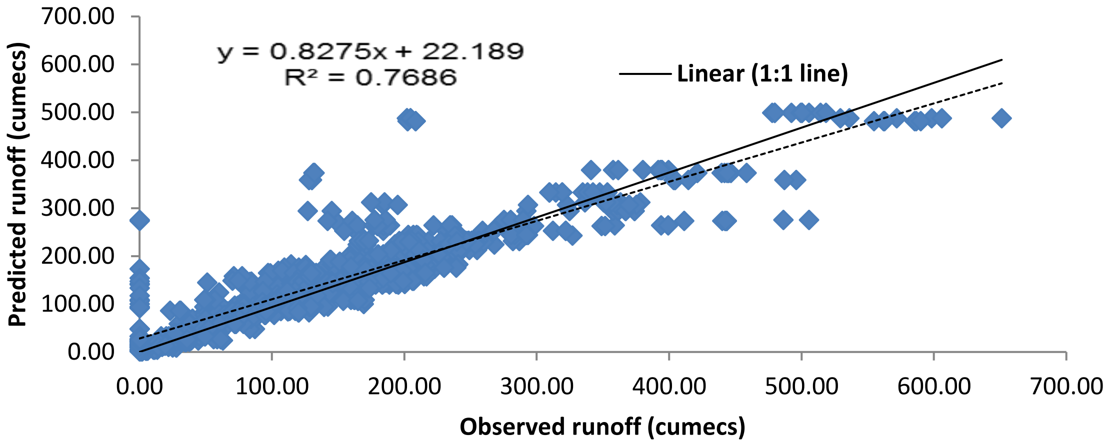

Fig. 3: Scatter plot of predicted and observed runoff for ANN-06 (6-18-18-1) model during training period for Mandla

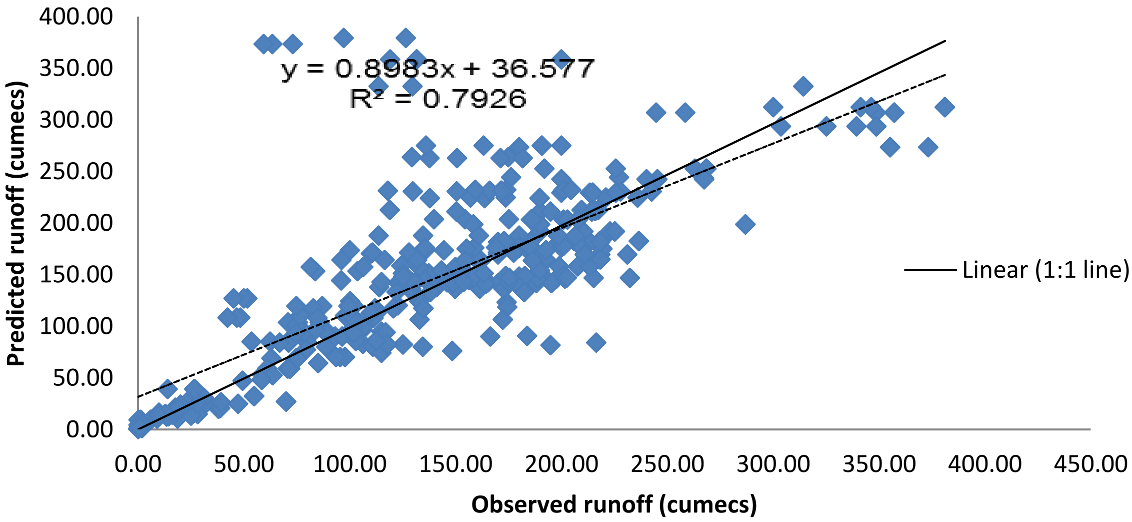

Fig. 4: Scatter plot of predicted and observed runoff for ANN-06 (6-18-18-1) model during testing period for Mandla

WANN based runoff prediction models for Mandla

The results obtained during training and testing are presented in Table 4. The Table 4 displayed the values of enhanced performance indicators for training and testing data which were used nomination of the runoff anticipated model. It can be observed for training and testing data values of RMSE, correlation coefficient, NSCE, WI, MAE and PARE varied from 0.793 to 1.104, 0.85 to 0.94, 0.79 to 0.85, 0.77 to 0.82, 2.1 to 4.1 and 1.1 -*10^{-3} to -0.80*10^{-3} . The analysis indicates that model WANN-06 having architecture (6-18-18-1) showed the best performance having utmost value of RMSE (1.104 cumec), uttermost value of correlation coefficient (0.94), maximum value of NSCE (0.85), maximum value of WI (0.82), supreme value of MAE (4.1) and value of PARE (1.1*10^{-3}).

Table 4: Key performance indicators for WANN (training and testing) based on runoff prediction models of Narsimhpur

Model	Architecture	Training RMSE (cumec)	r	NSCE	PARE (10^{-3})	WI	MAE	Testing RMSE (cumec)	r	NSCE	PARE (10^{-3})	WI	MAE
WANN-01	6-3-3-1	0.793	0.92	0.80	-7.8	0.80	7.1	1.019	0.80	0.69	-5.4	0.72	6.1
WANN-02	6-6-6-1	0.821	0.91	0.82	-7.2	0.82	7.2	1.048	0.79	0.70	-5.3	0.73	6.2
WANN-03	6-9-9-1	0.849	0.92	0.83	-7.3	0.72	7.3	1.076	0.77	0.71	-2.4	0.71	6.3
WANN-04	6-12-12-1	0.990	0.89	0.86	-7.1	0.73	7.8	1.104	0.73	0.72	-2.3	0.70	6.4
WANN-05	6-15-15-1	1.019	0.88	0.88	-2.1	0.83	7.3	0.963	0.77	0.70	-3.4	0.69	1.2
WANN-06	6-18-18-1	0.651	0.93	0.89	0.80	0.80	2.1	0.9061	0.84	0.73	-1.5	0.73	2.1
WANN-07	6-21-21-1	0.679	0.90	0.82	-2.3	0.76	2.2	1.104	0.82	0.70	-5.2	0.66	3.1
WANN-08	6-24-24-1	0.707	0.89	0.83	-3.2	0.75	3.2	1.076	0.80	0.62	-5.3	0.67	3.2
WANN-09	6-27-27-1	0.736	0.88	0.80	-3.3	0.74	3.3	1.1327	0.76	0.63	0.56	0.65	3.3
WANN-10	6-30-30-1	0.765	0.86	0.77	-3.4	0.72	4.5	1.1609	0.74	0.64	-3.2	0.66	3.4
WANN-11	6-33-33-1	0.793	0.87	0.79	-3.2	0.73	4.6	1.189	0.75	0.65	-3.1	0.67	3.5
WANN-12	6-36-36-1	0.821	0.88	0.77	-3.1	0.71	4.4	1.1327	0.76	0.66	-3.0	0.65	2.1
WANN-13	6-39-39-1	0.849	0.85	0.75	-3.0	0.70	4.3	1.189	0.77	0.67	-3.3	0.63	2.2
WANN-14	6-42-42-1	0.906	0.86	0.86	-4.1	0.75	4.5	1.104	0.73	0.62	-3.6	0.70	

Table 5: Key performance indicators for WANN (training and testing) based on runoff prediction models of Mandla

Model	Architecture	Training RMSE (cumec)	r	NSCE	PARE (10^{-3})	WI	MAE	Testing RMSE (cumec)	r	NSCE	PARE (10^{-3})	WI	MAE
WANN-01	6-3-3-1	0.849	0.80	0.77	-2.1	0.73	5.1	1.133	0.92	0.82	-3.1	0.77	4.3
WANN-02	6-6-6-1	0.906	0.82	0.76	-2.3	0.72	5.4	1.218	0.93	0.83	-3.3	0.76	4.5
WANN-03	6-9-9-1	0.877	0.83	0.73	-2.4	0.71	5.3	1.246	0.90	0.81	-3.5	0.80	4.3
WANN-04	6-12-12-1	1.019	0.81	0.75	-2.5	0.70	5.6	1.274	0.91	0.80	-3.8	0.79	4.2
WANN-05	6-15-15-1	0.930	0.82	0.74	-2.3	0.69	3.2	1.189	0.90	0.82	-3.9	0.77	4.3
WANN-06	6-18-18-1	0.793	0.85	0.79	-1.1	0.77	2.1	1.104	0.94	0.85	-0.80	0.82	4.1
WANN-7	6-21-21-1	0.821	0.80	0.77	-1.2	0.76	2.5	1.133	0.91	0.82	-0.90	0.81	2.1
WANN-08	6-24-24-1	0.906	0.79	0.75	-1.3	0.75	3.5	1.189	0.90	0.80	0.56	0.79	2.3
WANN-09	6-27-27-1	0.877	0.77	0.76	-3.1	0.74	3.3	1.161	0.89	0.81	0.28	0.77	2.5
WANN-10	6-30-30-1	0.930	0.76	0.72	-3.3	0.73	3.2	1.133	0.88	0.82	0.26	0.75	3.1
WANN-11	6-33-33-1	0.906	0.74	0.73	-3.4	0.72	3.7	1.274	0.82	0.83	-3.5	0.76	3.5
WANN-12	6-36-36-1	0.930	0.75	0.70	-2.1	0.71	3.8	1.303	0.83	0.80	-3.6	0.72	4.2
WANN-13	6-39-39-1	0.963	0.77	0.71	-2.2	0.70	3.6	1.330	0.85	0.81	-2.1	0.73	4.5
WANN-14	6-42-42-1	0.930	0.76	0.72	-2.3	0.72	4.5	1.359	0.86	0.82	-2.2	0.72	4.6

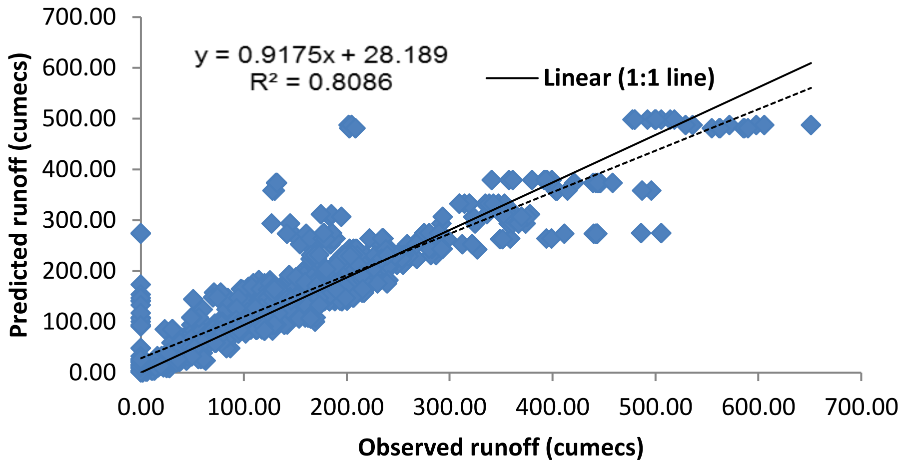

Fig. 5: Scatter plot of predicted and observed runoff for WANN-06 (6-18-18-1) model during training period for Narsimhpur

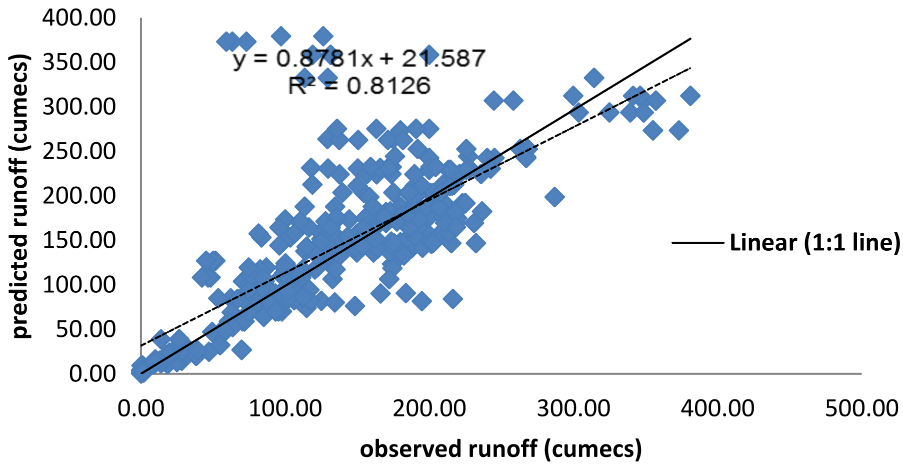

Fig. 6: Scatter plot of predicted and observed runoff for WANN-06 (6-18-18-1) model during testing period for Narsimhpur

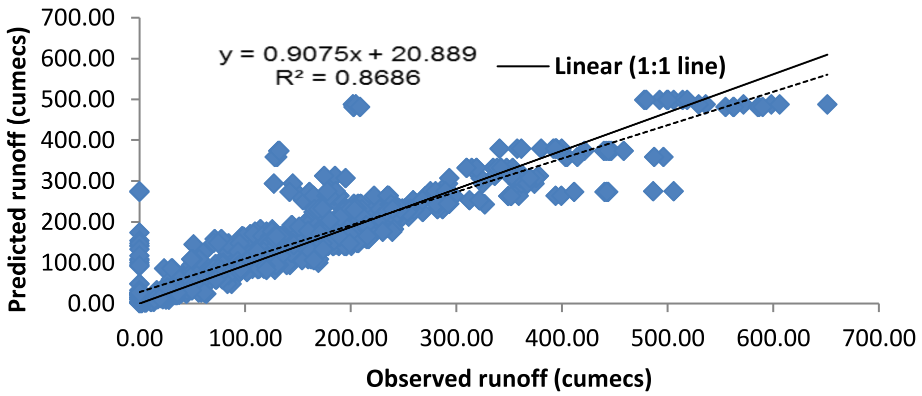

Fig. 7: Scatter plot of predicted and observed runoff for WANN-06 (6-18-18-1) model during training period for Mandla

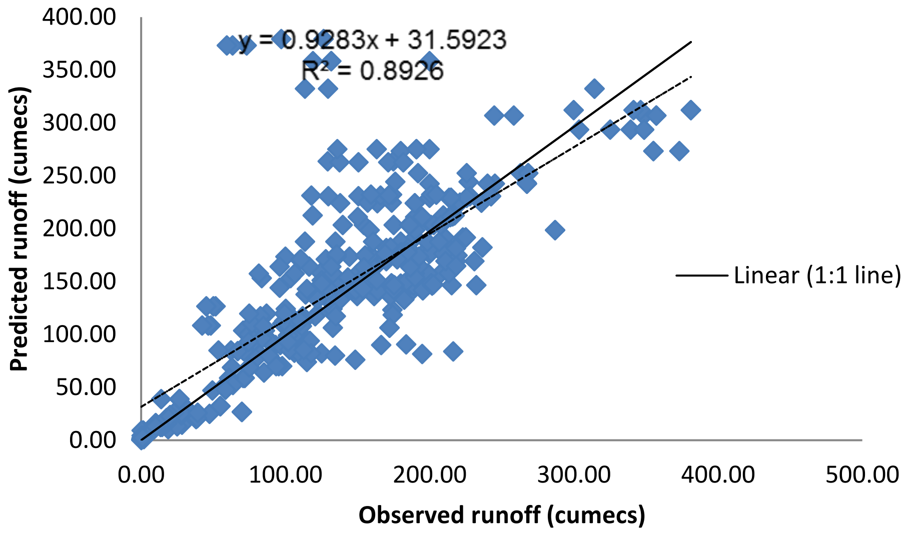

Fig. 8: Time series and scatter plots of predicted and observed runoff for WANN-06 (6-18-18-1) model during testing period for Mandla

CONCLUSION

Water resources are affected by parts of the atmosphere, lithosphere, and hydrosphere, including both living and non-living organisms on Earth. As water availability across the planet varies by location and time, it has been studied by researchers due to the limited quantity of pure water present. The quantity of water available on Earth is currently being placed under heavy stress due to high demand and limited availability. Sustainable water management is required to ensure that the gap between demand and supply of water resources is narrowed.

In the present work, runoff generated by rainfall was estimated using various approaches for functional analysis. Rainfall and corresponding runoff data spanning 12 years (2010–2021) for Narsinghpur and Mandla were collected during the monsoon season (June, July, August, and September) from the Water Resource Information System website. Runoff data (in cumec) and rainfall data (in mm) were obtained. A Gamma test was conducted to recognize the optimal data combinations for the enhancement various rainfall-runoff models. Input variables were selected as rainfall at time t, rainfall at time t–1, runoff at time t–1, runoff at time t–2, and runoff at time t–3. Runoff at time t was considered as the output.

Optimum results for model development and validation were provided by the ANN model with the architecture 6-18-18-1. Similarly, optimum results for both training and testing were achieved by the WANN model with the same architecture. On average, better correlation coefficients, lower mean square errors, and reduced pooled average relative errors were yielded by WANN models. Additionally, higher Nash–Sutcliffe efficiency and greater Willmott index values were obtained in comparison to ANN models. These outcomes can be utilized for runoff forecasting across various applications such as irrigation, flood control, and related water management strategies.

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Genetic divergence and yield trait impact in French Bean (*Phaseolus vulgaris* L.)

BHAWANA MAMGAIN[1*], B.P. NAUTIYAL [2], S.C. PANT[3], VAISAHLI THAPA[4], HEIGRUJAM RIYASANA[5] and MAYANK[6]

[1,4,5&6] Institute of Agriculture Training and Research, Dehradun-248001, [2] Basic Science and Humanity, Uttarakhand University of Horticulture and Forestry- 246285, [3] Department of Breeding Uttarakhand University of Horticulture and Forestry- 246285 (Uttarakhand)

**Corresponding author's email id: 56682_bhawanamamgai@gbpuat-tec.ac.in*

ABSTRACT: The present investigation was undertaken to study Genetic Divergence and Yield Trait Impact in French Bean (*Phaseolus vulgaris* L.). The experiment was conducted at the Vegetable Research and Demonstration Block, Department of Vegetable Science, College of Horticulture, VCSG Uttarakhand University of Horticulture and Forestry, Bharsar, Pauri Garhwal (Uttarakhand). A total of 24 genotypes were evaluated in a randomized block design with three replications. Genotypic correlation coefficients were estimated to determine associations among yield and its component traits, while path coefficient analysis was employed to partition correlations into direct and indirect effects on seed yield per plant. Genetic divergence among genotypes was grouped the genotypes into four distinct clusters, indicating substantial genetic variability. The maximum inter-cluster distance was observed between Cluster I (D^2 = 2.920) and Cluster III (D^2 = 5.571), reflecting the highest level of genetic divergence. Seed weight, number of primary branches per plant, and seed yield per plot exhibited strong positive direct effects on seed yield per plant and this shows their importance as selection criteria. The identified genetically divergent clusters and key yield-influencing traits can be effectively utilized in future French bean breeding programmes for yield improvement.

Keywords: Components, Correlation analysis, Genetic divergence, French bean, Path coefficient analysis, Yield

French bean (*Phaseolus vulgaris* L.) is one of the most important grain and vegetable legumes cultivated across temperate, subtropical, and tropical regions of the world. It is valued for its tender green pods and dry seeds, which are rich sources of protein, dietary fibre, vitamins, and essential minerals, thereby contributing significantly to nutritional security and farm income (Singh, 2001; Beebe *et al.,* 2013).

Despite its economic importance, the productivity of French bean remains relatively low, largely due to a narrow genetic base and the complex inheritance of yield and its component traits. Seed yield is a polygenic trait governed by several interrelated morphological and physiological characters, whose expression is strongly influenced by environmental conditions (Rana *et al*., 2015). Consequently, direct selection for yield alone is often ineffective, necessitating an understanding of the relationships among yield-contributing traits.

Correlation analysis provides information on the degree and direction of association among characters but does not reveal their true cause effect relationships (Falconer and Mackay, 1996). Path coefficient analysis, originally proposed by Wright (1921) and later refined by Dewey and Lu (1959), addresses this limitation by partitioning correlation coefficients into direct and indirect effects, thereby identifying traits that exert a real and substantial influence on yield. The usefulness of correlation and path analysis in defining effective selection criteria for yield improvement in French bean and related legumes has been well documented (Dutta *et al*., 2018; Santos *et al*., 2017).

Genetic divergence analysis using Mahalanobis D^2 statistics further complements these approaches by assessing genetic diversity and classifying genotypes into distinct clusters to identification of genetically divergent parents is essential for exploiting heterosis and generating broad variability in segregating populations (Singh, 2001). However, information integrating genetic divergence, character association, and path coefficient analysis in French bean under the mid-hill agro-climatic conditions of Uttarakhand is limited. The unique environmental conditions of this region, characterized by moderate temperatures and variable rainfall, may significantly influence trait expression and interrelationships, making region-specific evaluation essential. Therefore, the present study was undertaken to analyze genetic divergence, correlation, and direct and indirect effects of yield-related traits in French bean genotypes under mid-hill conditions of Uttarakhand, with the objective of identifying key selection traits and genetically diverse parents for future breeding programmes.

MATERIALS AND METHODS

The present investigation was carried out during the kharif season of 2018-2019 at the Vegetable Research and Demonstration Block, Department of Vegetable Science, College of Horticulture, VCSG Uttarakhand University of Horticulture and Forestry, Bharsar, Pauri Garhwal, Uttarakhand. The experimental site represents the mid-hill agroclimatic conditions of Uttarakhand, characterized by moderate temperature and variable rainfall, and is well suited for French bean cultivation.

A total of 24 French bean genotypes, comprising released varieties and germplasm accessions, were evaluated during the cropping season. The experiment was laid out in a Randomized Block Design (RBD) with three replications. The plots of size 3m × 1m and each genotype was grown in individual plots at the spacing 100cm × 50cm. Observations were recorded on growth, phenological, yield, and quality-related traits. The characters studied included days to germination, days to first flowering, days to 50% flowering, days to first harvest, pod maturity duration, plant height (cm), number of primary branches per plant, number of pods per plant, pod length (cm), pod diameter (cm), number of seeds per pod, average pod weight (g), 100-seed weight (g), seed yield per plant (g), seed yield per plot (kg), and protein content (%). Observations were recorded from five randomly selected plants in each plot, and the mean values were used for statistical analysis. Protein content of dry seeds was determined by estimating the nitrogen content as per the modified Kejldhal's method (Jackson, 1965) and multiplying it with the factor 6.25 (Dubetz and Wells, 1968) and expressed on percent basis for each genotype.

Genotypic correlation coefficients were computed to assess the association among different traits following the procedure outlined by Al-Jibouri *et al.* (1958). Path coefficient analysis was performed according to the method suggested by Wright (1921) and elaborated by Dewey and Lu (1959) to partition correlation coefficients into direct and indirect effects on seed yield per plant. Genetic divergence among genotypes was estimated using Mahalanobis D^2 statistics (Mahalanobis, 1936), and clustering of genotypes was carried out using Tocher's method to determine the pattern of genetic diversity. All statistical analyses were performed using SPSS and R software.

RESULTS AND DISSCUSSION

The genetic divergence analysis based on Mahalanobis D^2 statistics grouped the 24 French bean genotypes into four distinct clusters (Table 1), indicating the presence of substantial genetic variability among the evaluated germplasm. Cluster IV accommodated the maximum number of genotypes (8), followed by Cluster III (7) and Cluster II (5), while Cluster I contained the minimum number of genotypes (4). The distribution of genotypes across clusters irrespective of their geographic origin suggests that genetic constitution rather than geographical collection influenced cluster formation, a trend widely reported in French bean diversity studies (Verma *et al.*, 2014).

The average intra-cluster distances were lower than the corresponding inter-cluster distances, reflecting greater homogeneity within clusters and pronounced divergence among clusters. Cluster III exhibited the lowest intra-cluster distance (2.598), indicating close genetic similarity among its genotypes, whereas Cluster I recorded the highest intra-cluster distance (2.920), suggesting comparatively greater variability within that cluster. Similar patterns of intra-cluster variation have been reported in D^2-based diversity analyses of common bean germplasm (Kumar, 2024).

Analysis of inter-cluster distances revealed varying degrees of genetic divergence among clusters. The maximum inter-cluster distance was observed between Cluster I and Cluster III (5.571), followed by Cluster I and Cluster IV (4.970) and Cluster I and Cluster II (4.853), indicating that genotypes belonging to these clusters are genetically most divergent. In contrast, the minimum inter-cluster distance occurred between Cluster II and Cluster III (3.758), reflecting closer genetic affinity between these groups. High inter-cluster distances are particularly important for breeding programmes, as crosses between genetically divergent parents are more likely to generate higher heterosis and wider variability in segregating populations (Chhetri *et al*., 2025).

Overall, the clustering pattern and magnitude of D^2 values confirm the existence of wide genetic divergence among the studied French bean genotypes, highlighting the availability of a broad genetic base that can be effectively exploited for selection and hybridization aimed at yield improvement (Verma *et al.,* 2014).

Table 1: Clustering pattern of 24 genotypes of French bean on the basis of genetic divergence

Clusters	No. of genotypes	Genotype name
I	4	Lakshmi, LC-2, Harsil LC-1, LC-1
		IC-049810, IC-199211, EC-755542, IC-
II	5	199208, EC- 755484
		EC-755510, Solan LC-1, Bean No.-2, IC-
III	7	84337, EC- 755478, EC-755480, IC-84376
IV	8	755444, EC-755508
		EC-755509, EC- 755455, EC-755477

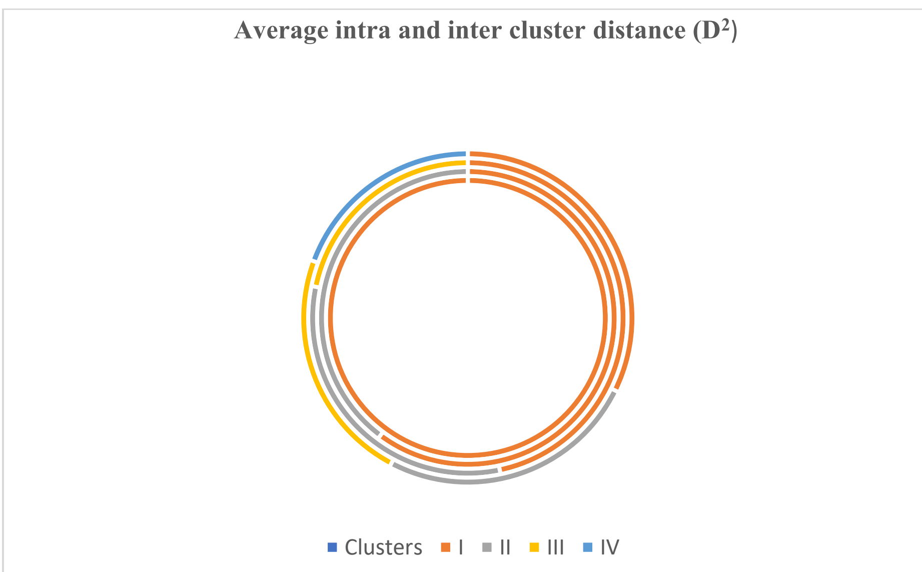

Fig. 1: Average intra and inter cluster distance (D^2)

Mean Performance: The cluster mean analysis revealed substantial variation among the four clusters for all sixteen characters studied, confirming the presence of wide genetic diversity among the French bean genotypes (Fig. 2). Differences in cluster means indicate the relative contribution of component traits to genetic divergence and their potential influence on yield expression, as commonly reported in multivariate diversity studies of grain legumes (Mahalanobis, 1936; Singh, 2001).

Cluster I recorded the lowest mean values for days to germination, days to 50% germination, days to first flowering, and days to 50% flowering, indicating its association with earliness. This cluster also exhibited the highest mean values for number of primary branches per plant, seed weight, protein content, seed yield per plant, and seed yield per plot. The superior yield performance of Cluster I may be attributed to the combined effect of earliness and favourable expression of yield-contributing traits, which has been reported to enhance productivity in French bean and related legumes (Dewey and Lu, 1959; Dutta *et al.,* 2018).

Cluster II showed moderate mean performance for most characters and recorded higher values for plant height, pod length, and number of seeds per pod. However, seed yield per plant and per plot were lower compared to Cluster I, suggesting that individual component traits alone may not directly translate into higher yield unless supported by other complementary traits. Similar observations have been reported in earlier studies on French bean (Santos *et al.,* 2017).

Cluster III was characterized by relatively later flowering, as indicated by higher mean values for days to first flowering and days to 50% flowering. Although this cluster exhibited a shorter pod set to pod maturity duration, it recorded the lowest seed yield per plant and per plot. The lower yield observed in this cluster may be associated with less favourable combinations of yield-contributing traits rather than any single physiological limitation, and therefore warrants further investigation.

Cluster IV represented late-flowering genotypes and exhibited comparatively higher plant height and moderate average pod weight. Seed yield per plant and per plot were second highest after Cluster I, indicating that delayed phenology does not necessarily limit yield potential when supported by favourable yield attributes. Such genotypes may be useful in breeding programmes aimed at broadening the genetic base and improving yield stability (Singh, 2001; Beebe *et al*., 2013).

Overall, the marked differences in cluster means for yield and related traits suggest that genotypes from genetically divergent clusters, particularly Cluster I in combination with Cluster III or Cluster IV, could be exploited in hybridization programmes to generate wider variability and improved yield potential. However, a more definitive understanding of trait contributions to seed yield requires explicit integration of correlation and path coefficient analyses, including the magnitude of direct and indirect effects of individual traits. The absence of detailed discussion on these relationships represents a limitation of the present study and highlights the need for their comprehensive interpretation alongside cluster mean performance.

CONCLUSION

Based on cluster mean performance, Cluster I emerged as the most promising group, characterized by earliness, higher number of primary branches, greater seed weight, superior protein content, and maximum seed yield per plant and per plot. These traits—particularly seed weight, number of branches per plant, and earliness parameters should be given priority as key selection criteria for yield improvement in French bean. Cluster IV, despite its relatively late flowering, also exhibited high yield potential and may serve as a valuable source of favorable yield attributes. Considering the magnitude of inter-cluster divergence and complementary trait expression, genotypes belonging to Cluster I in combination with those from Cluster III or Cluster IV are recommended for hybridization programmes. Such crosses are expected to generate greater heterosis and wider variability in segregating generations, facilitating the development of high-yielding and nutritionally superior French bean varieties. Overall, the findings provide clear trait-based selection guidelines and parent combinations that can be effectively utilized in future French bean breeding efforts.

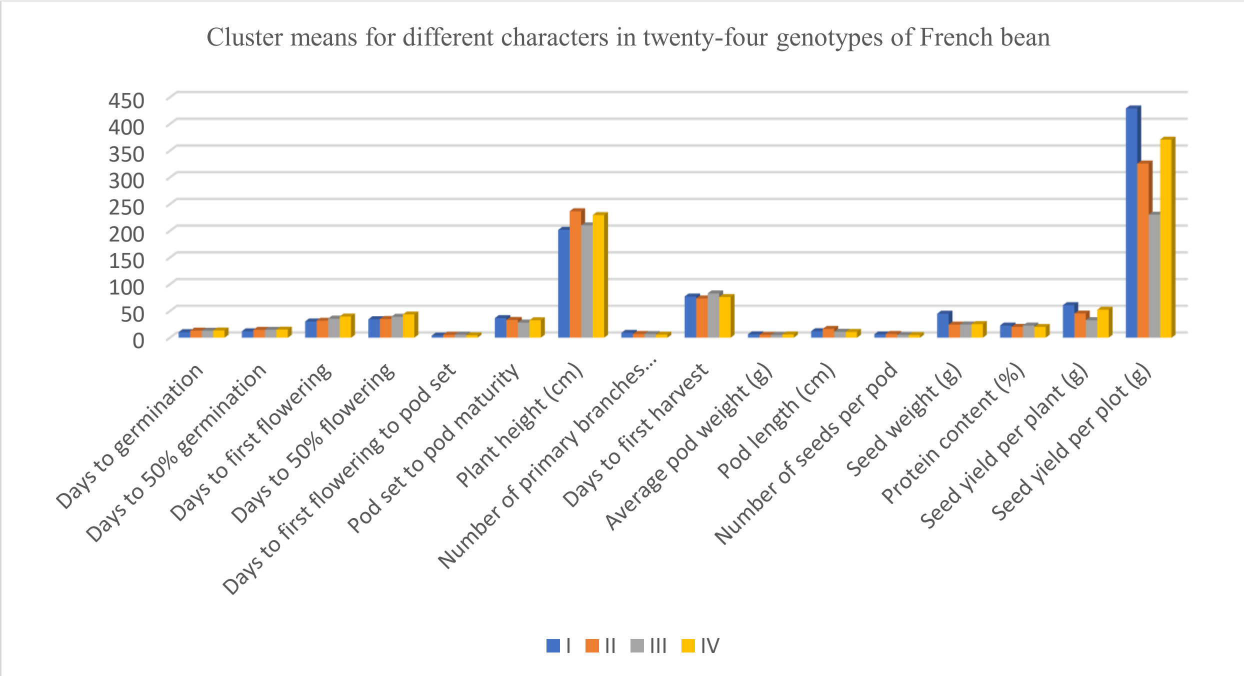

Fig. 2: Cluster means for different characters in twenty-four genotypes of French bean

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Natural Farming Inputs (NFIs) as sustainable alternatives for enhancing the growth and development of Chickpea (*Cicer arietinum* L.)

SHAIFALI[1] and A.K. SHARMA[2]

[1]Department of Biological Sciences, College of Basic Sciences and Humanities, G. B. Pant University of Agriculture and Technology, Pantnagar-263145 (U. S. Nagar, Uttarakhand), [2]Sri Sri University, Cuttack -754006
**Corresponding author's email id: shaifaliazad@gmail.com*

ABSTRACT: Natural farming is an ecologically sustainable production system that relies on locally available biological resources to improve soil health, crop growth and agro-ecosystem resilience while minimising dependence on chemical inputs. The present study evaluated the effectiveness of selected natural farming inputs (NFIs), namely Panchagavya, Jeevamruth and Amritpani on the growth and development of chickpea (*Cicer arietinum* L.) cultivar PG-186 under greenhouse conditions. Eleven treatments were assessed, and all NFI-based applications significantly enhanced plant growth compared to the control and farmyard manure (FYM). Among the evaluated inputs, Panchagavya proved most effective, resulting in superior biomass accumulation, nutrient uptake and biochemical attributes. Notably, Panchagavya application significantly increased plant height (54.51 ± 1.19 cm), fresh biomass (9.27 g) and dry biomass (3.05 g) over the control. Overall, the results highlight the potential of NFIs, particularly Panchagavya, as sustainable and efficient alternatives to conventional inputs for improving chickpea growth and productivity.

Keywords: Amritpani, Chickpea, Jeevaamruth, Panchagavya, Sustainable Yield

Natural farming is an ancient yet regenerative agricultural approach grounded in ecological interaction among soil, crops, livestock and microorganisms aimed at developing self-sustaining agro-ecosystems (Sharma *et al*., 2023). This system enhances soil fertility and overall soil health through the incorporation of beneficial microbial communities and organic resources, thereby reducing reliance on synthetic fertilisers. In recent years, natural farming has gained considerable attention and adoption in India as well as globally due to its sustainability and environmental benefits (Duddigan *et al*., 2022). The use of organic inputs such as farmyard manure, compost, neem cake, vermicompost and poultry manure has long been practiced as a viable alternative to chemical fertilisers, contributing to nutrient supply, soil organic carbon maintenance, and favourable soil physical conditions (Kumar *et al*., 2020; Islam *et al*., 2024). Recent advancements in natural farming emphasize the use of fermented liquid bio-inputs and effective microorganisms, particularly formulations derived from cow dung and urine, to increase nutrient availability, microbial activity and crop productivity (Sarma *et al*., 2024).

Natural farming inputs (NFIs) such as panchagavya, jeevamruth, and amritpani are widely used bovine-based fermented preparations that improve soil structure, microbial diversity and rhizospheric interactions. These inputs contain diverse microbial consortia, including nitrogen-fixing, phosphate-solubilising and plant growth–promoting microorganisms, which facilitate nutrient cycling, root development, plant vigour, and yield stability while reducing dependency on chemical agrochemicals (Gohil *et al*., 2023). Chickpea (*Cicer arietinum* L.), a major pulse crop of the Fabaceae family, is a vital source of plant-based protein, minerals, and micronutrients, particularly in semi-arid and temperate regions. Globally, chickpea ranks second in acreage and third in production among pulse crops, with India contributing the largest share of the estimated 11.5 million tonnes annual production (Merga and Haji, 2019). Given its nutritional and economic importance, the present study aimed to evaluate the individual effects of selected NFIs on the growth and development of chickpea under controlled conditions, with a focus on their microbial efficacy and potential as sustainable alternatives to conventional fertilisation practices.

MATERIALS AND METHODS

Experiment design

A pot experiment was conducted under controlled glasshouse conditions in the Department of Biological Sciences to evaluate the effects of natural farming inputs (NFIs), their microbial communities (MC), and microbial-free filtrates (MFF) on chickpea growth. The experiment was maintained at a temperature of 25–28°C with a 16/8 h light–dark photoperiod and approximately 60% relative humidity. Pots (2 kg capacity) were filled with a sterilised sand-soil mixture (3:1, w/w) having a pH of 7.15 and electrical conductivity of 65.1 µS. Four surface-sterilised seeds of chickpea (*Cicer arietinum* L.) cultivar PG-186 were sown per pot. At 15 days after sowing, seedlings were treated with the respective natural farming inputs (NFIs), microbial communities, and microbial-free filtrates through soil drenching, with 50 mL applied to each pot. Plants were harvested 45 days after treatment for physiological, biochemical, and nutrient analyses. The experiment comprised of eleven treatments: Control (T_1); Farm Yard manure(T_2); Panchagavya (T_3); Panchagavya microbial community (T_4); Panchagavya microbial-free filtrate (T_5); Jeevamruth (T_6); Jeevamruth microbial community (T_7); Jeevamruth microbial-free filtrate (T_8); Amritpani (T_9); Amritpani microbial community (T_{10}) and Amritpani microbial-free filtrate (T_{11}). Each treatment was replicated three times and arranged in a completely randomized block design.

Preparation of NFIs, MC and MFF

Panchagavya, Jeevamruth, and Amritpani were prepared following the methods described by Jain *et al*. (2014), Maity *et al*. (2020) and Shekh *et al*. (2018). For microbial communities (MC) preparation, 10 mL of each NFI was inoculated into 40 mL of N+P medium (nutrient broth and potato dextrose broth) and incubated at 27°C for 24 h, maintaining an optical density (OD) of 0.1. For microbial-free filtrate (MFF) preparation, each NFI was centrifuged at 12,000 rpm, the supernatant was filtered through Whatman No. 1 filter paper to remove debris, and subsequently passed through a 0.22 µm membrane filter under vacuum to eliminate associated microorganisms.

Plant Growth Characteristics

Plants were harvested 45 days after treatment and thoroughly washed with tap water to remove adhering soil particles. Root and shoot lengths, along with fresh biomass, were recorded. Dry matter accumulation was determined after oven-drying the samples at 65°C for 24 h.

Biochemical analysis

Estimation of Chlorophyll

Leaf chlorophyll content was estimated following Arnon (1949) by homogenising 0.1 g fresh leaf tissue in 10 mL of 80% acetone, incubating in the dark for 24 h, and recording absorbance at 663 nm (*Chl a*) and 645 nm (*Chlb*).

Estimation of Phosphorus and Potassium

Phosphorus content was estimated using the vanadomolybdate reagent method as described by Jackson (1973) and further detailed by Sharma and Sharma (2019). Potassium content was measured using a flame photometer Sharma and Sharma, (2019).

Statistical analysis

All data are expressed as mean ± standard error (SE), with three replicates per treatment (n = 3). Plant growth and biochemical parameters were analysed using one-way analysis of variance (ANOVA). Treatment means were separated using Tukey's honestly significant difference (HSD) test at a significance level of $p < 0.05$.

RESULTS AND DISCUSSION

Effect of NFIs on vegetative characters

Shoot length, Shoot fresh and dry weight

The application of natural farming inputs (NFIs) significantly improved vegetative growth parameters of chickpea compared to the control and farmyard manure treatments. Among the evaluated NFIs, Panchagavya (T_3) produced the maximum shoot length (54.51 ± 1.19 cm), showing statistically significant results over all other treatments (Table 1). This was followed by Panchagavya microbial communities (T_4; 50.33 ± 0.57 cm) and Jeevamruth (T_6; 49.01 ± 0.71 cm), which were statistically comparable and markedly higher than the remaining treatments. The enhanced shoot elongation under Panchagavya application may be attributed to the presence of bioactive compounds, enzymes, and growth-promoting substances that stimulate cell division and elongation (Panchal *et al*., 2017). Similarly, Panchagavya application resulted in the highest shoot fresh weight (9.27 g) and dry weight (3.05 g), which were significantly superior to all other treatments (Table 1). The Panchagavya microbial community (T_4) ranked second, recording fresh and dry weights of 7.42 g and 2.08 g, respectively. The observed increase in biomass under Panchagavya and its microbial formulations can be ascribed to the availability of essential nutrients and growth-promoting metabolites that enhance biomass accumulation and overall plant vigour (Panda *et al*., 2020).

Table 1: Effect of NFIs on vegetative growth of chickpea cultivar PG-186

Treatment	Plant length (cm)	Plant fresh weight (g)	Plant dry weight (g)	Root length (cm)	Root fresh weight (g)	Root dry weight (g)
T_1: Control	30.49±0.98a	3.14±0.09a	0.92±0.04a	16.66±0.33a	1.10±0.03a	0.37±0.02a
T_2: Fram Yard manure	36.00±0.60b	5.29±0.13b	1.09±0.04b	22.09±0.07b	1.37±0.02a	0.42±0.01a
T_3: Panchagvya	54.51±1.19f	9.27±0.04g	3.05±0.10h	30.97±0.49g	4.35±0.03f	0.95±0.01f
T_4: Panchagvya microbial Communities	50.33±0.57e	7.42 ±0.28f	2.08±0.03g	27.47±0.18f	3.55±0.19e	0.84±0.01d
T_5: Panchagvya microbial free filtrate	44.02±1.02cd	6.16±0.07ef	1.84±0.03f	25.36±0.22cde	2.99±0.03d	0.67±0.02c
T_6: Jeevamruth	49.01±0.71e	6.88±0.07ef	1.69±0.02e	28.15±0.62f	2.93±0.03d	0.82±0.004de
T_7: Jeevamruth microbial communities	46.53±0.84de	5.90±0.04cd	1.52±0.01ef	26.08±1.53def	2.82±0.08cd	0.74±0.03d
T_8: Jeevamruthmicrobial free filtrate	38.46±0.67b	5.87±0.06cd	1.36±0.03cd	24.70±0.64bc	2.56±0.03c	0.67±0.02c
T_9: Amritpani	47.40±0.56de	6.84±0.06ef	1.42±0.02cd	25.74±0.84de	2.90±0.01d	0.76±0.03de
T_{10}: Amritpani microbial communities	39.87±1.01bc	6.21±0.36d	1.25±0.02bc	23.40±0.36bcd	1.92±0.04b	0.68±0.02c
T_{11}: Amritpani microbial free filtrate	37.57±0.73b	5.41±0.11b	1.15±0.01b	22.25±0.12bcde	1.75±0.02b	0.54±0.01b
SD(m)	0.83	0.15	0.039	0.63	0.06	0.01
CD(5%)	2.45	0.45	0.11	1.87	0.20	0.053

All parameters are presented as mean ± standard error (n = 3). Different superscript letters indicate significant differences ($P < 0.05$) among treatments, while identical letters denote no significant difference

Root length, Root fresh and dry weight

Application of Panchagavya (T_3) resulted in maximum root length (30.97 cm), followed by Jeevamruth (T_6; 28.15 cm). The Panchagavya-derived microbial community (T_4) also significantly enhanced root elongation (27.47 cm), reflecting a strong stimulatory effect on root system development. The increased root extension observed across all NFI treatments (Table 1) suggests that these inputs act as nutrient-rich substrates that promote root proliferation. As reported by Hodge *et al*. (2004), plant roots respond to localised nutrient enrichment by increasing elongation and branching to optimise nutrient uptake. Panchagavya (T_3) also recorded the highest root fresh weight (4.35 g) and dry weight (0.95 g), followed by the Panchagavya microbial community (T_4), which yielded fresh and dry weights of 3.55 g and 0.84 g, respectively. Overall, Panchagavya and its associated microbial community were most effective in increasing root biomass, highlighting their potential to stimulate root growth and development. The improved root architecture observed under Panchagavya treatment likely facilitated greater water and nutrient uptake, contributing to enhanced plant vigour (Chaudhari *et al*., 2023). Furthermore, the balanced nutrient composition of these inputs ensures adequate availability of essential elements necessary for optimal plant growth, physiological processes and overall development (Singh *et al*., 2024).

Effect of NFIs on chlorophyll content in chickpea

Panchagavya (T_3) showed a pronounced positive effect on chlorophyll accumulation in chickpea (Table 2), leading to a significant increase in both chlorophyll *a* and chlorophyll *b* contents. The enhanced concentration of photosynthetic pigments under Panchagavya treatment may be associated with the presence of plant growth–promoting phytohormones, particularly kinetin, which plays a key role in chlorophyll synthesis and stability. The inclusion of coconut water during Panchagavya preparation, a known source of kinetin, likely contributed to the elevated chlorophyll content observed in this study (Khatua *et al*., 2025).

Table 2: Effect of NFIs on chlorophyll content and phosphorus and potassium uptake

Treatments	Chl*a* (mg/g FW)	Chl*b* (mg/g FW)	Nutrients% Phosphorus%	Potassium%
T_1: Control	0.49±0.009a	0.25±0.003a	1.38±0.02a	1.95±0.07a
T_2: Fram Yard manure	0.62±0.006b	0.30±0.005b	1.92±0.02b	3.04±0.02b
T_3: Panchagavya	1.11±0.01h	0.74±0.007g	4.12±0.02g	5.25±0.10i
T_4: Panchagavya microbial Communities	1.00±0.013gh	0.49±0.008ef	3.66±0.08f	4.51±0.06gh
T_5: Panchagavya microbial-free filtrate	0.89±0.019d	0.42±0.01cd	2.57±0.05d	4.04 ±0.10ef
T_6: Jeevamruth	1.06±0.006gh	0.52±0.004f	3.59±0.05f	4.07±0.07h
T_7: Jeevamruth microbial communities	0.97±0.003ef	0.48±0.002de	2.89±0.06e	3.61±0.10de
T_8: Jeevamruthmicrobial-free filtrate	0.88±0.006de	0.40±0.025cd	2.05±0.04c	3.14±0.06cd
T_9: Amritpani	1.00±0.021gh	0.44±0.009d	3.09±0.05e	4.57±0.08fg
T_{10}: Amritpani microbial communities	0.83±0.003d	0.42±0.015cd	2.18±0.03c	3.78±0.07def
T_{11}: Amritpani microbial-free filtrate	0.73±0.02c	0.36±0.009bc	2.17±0.03c	3.56±0.18bc
SD(m)	0.012	0.011	0.045	0.08
CD (5%)	0.03	0.03	0.13	0.26

All parameters are presented as mean ± standard error (n = 3). Different superscript letters indicate significant differences ($P < 0.05$) among treatments, while identical letters denote no significant difference

Effect of NFIs on phosphorus and potassium uptake in chickpea

Phosphorus and potassium uptake data are presented in Table 2. Among the evaluated natural farming inputs, Panchagavya (T_3) proved to be the most effective bio-nutrient source, resulting in the highest phosphorus (4.12±0.02%) accumulation in chickpea plants. Enhanced phosphorus content was also observed under the Panchagavya-derived microbial community (3.66%) and Jeevamruth (3.59%) treatments. Similarly, Panchagavya-treated plants recorded the maximum potassium content (5.25%), followed by Amritpani (4.57%) and the Panchagavya microbial community (4.51%), highlighting their strong influence on potassium uptake. These results align with earlier findings by Beaulah (2002), who reported that the integrated application of Panchagavya with organic amendments such as poultry manure and neem cake significantly improved nutrient concentrations in *Moringa oleifera* leaves and pods.

CONCLUSION

The present study demonstrates that natural farming inputs (NFIs) serve as effective and sustainable alternatives for improving the growth and development of chickpea under glasshouse. Application of NFIs, including their microbial communities and microbial-free filtrates, significantly enhanced shoot and root growth, biomass accumulation, and overall biochemical health compared to the control and farmyard manure. Among the treatments, Panchagavya and its associated microbial communities exhibited the greatest growth-promoting effects, followed by Jeevamruth. The superior performance of Panchagavya is attributed to its rich consortium of beneficial microorganisms and bioactive metabolites derived from cow-based components. Overall, the findings highlight the microbial- and metabolite-mediated functionality of NFIs and confirm their potential to enhance chickpea productivity and resilience in sustainable agricultural systems.

Future perspectives

While the present study was conducted under controlled glasshouse conditions, future research should focus on multi-season field validation to assess the consistency and scalability of NFI-mediated benefits under diverse soil and climatic conditions. Molecular characterisation of the microbial communities associated with Panchagavya and Jeevamruth using metagenomics or amplicon sequencing would provide deeper insights into key functional taxa responsible for metabolite production and plant growth promotion. Additionally, metabolomic profiling of NFIs and rhizosphere soils could help identify specific bioactive compounds responsible for the observed physiological and biochemical improvements. Such integrated microbial and metabolite-based approaches will strengthen the scientific basis of natural farming inputs and support their wider adoption in sustainable and climate-resilient agricultural systems.

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