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Stream Flow Forecasting Using Least Square Support Vector Regression

S.N. Londhe[1*], S. Gavraskar[2]

1. Professor, Vishwakarma Institute of Information Technology, Pune, India
2. PG Student, Vishwakarma Institute of Information Technology, Pune, India

Corresponding author: *shreenivas.londhe@viit.ac.in*

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ABSTRACT

Accurate forecasting of streamflow for different lead-times is useful in the design of almost all hydraulic structures. The Support Vector Machines (SVMs) use a hypothetical space of linear functions in a kernel-induced higher dimensional feature space and are trained with a learning algorithm from optimization theory. The support vector regression attempts to fit a curve on data points such that the points lie between two marginal hyperplanes which will minimize the error. The current paper presents least square support vector regression (LS-SVR) to predict one day ahead stream flow using past values of the rainfall and river flow at three stations in India, namely Nighoje and Budhwad in Krishna river basin and Mandaleshwar in Narmada river basin. The relevant inputs are finalized on the basis of three techniques namely autocorrelation, Cross-correlation and trial and error. The forecasting model results are reasonable as can be seen from a low value of Root Mean Square Error (RMSE), Mean Absolute Relative Error (MARE) and high values of Coefficient of Efficiency (CE) accompanied by balanced scatter plots and hydrographs.

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1. Introduction

Water is one the most abundant substance on earth, the principal constituent of all living things, and the major force constantly shaping the earth. Water resources play a vital role in the economic development. The region's explosive population growth and resulting new demands on limited water resources require efficient management of existing water resources rather than building new facilities to meet the challenge. In the water management communities, it is well known that to combat water shortage issues, maximizing water management efficiency based on streamflow forecasting is crucial [1]. The rainfall-runoff (RR) relationship is amongst the most complex hydrologic phenomenon to understand due to the incredible spatial and temporal variability of watershed characteristics and precipitation patterns, as well as a number of variables involved in the physical processes. Many models have been developed to simulate rainfall-runoff processes but still require refinement for their predictions [2].

The classification of rainfall-runoff models is generally based on the extent of physical principles that are applied in the model structure and the treatment of the model inputs and parameters as a function of space and time. According to the physical process description, a rainfall-runoff model can be attributed to two categories, deterministic and stochastic. Deterministic models describe the rainfall-runoff process using physical laws of mass and energy transfer. Deterministic models can be classified according to a lumped or distributed description of the sub-catchment area under consideration and description of the hydrological processes as empirical, conceptual or more physically based. On this basis deterministic rainfall-runoff models are further classified as: (i) data-driven models (black box), (ii) conceptual models (grey box) and (iii) physically based models (white box) [3]. If any of the input-output variables or error terms of the model are regarded as random variables having a probability distribution, then the model is stochastic. Readers are referred to [4] for further details of rainfall-runoff modeling. The Support Vector Regression (SVR) used in the present study can be classified as a lumped data-driven model.

In the present study forecasting streamflow at three different stations namely Mandaleshwar, Budhwad and Nighoje in India are done using Least square support vector regression (LS-SVR) and previous values of rainfall and stream flow. The inputs for the models are finalized with three different input selection methods namely Trial and Error, Average Mutual Information (AMI) and Correlation Analysis. Four different data division combinations are tried to get optimum result. The support vector regression (SVR) models are calibrated with three different kernels namely Radial Basis Function, Linear, and Polynomial. The best model is finalized by comparing results by various error measures along with scattering plot and hydrograph. The paper is organized as follows: The next two sections introduce support vector machine and support vector regression along with literature review of the application of SVR for streamflow forecasting. This is followed by information on Study Area and Model formulation. Results and discussions come next with concluding remarks at the end.

2. Study area and data

The present work deals with forecasting of streamflow one day in advance at three stations namely Mandaleshwar in Narmada river basin and Nighoje and Budhwad in Krishna river basin of India using previous values of both rainfall and stream flow. The Narmada, the largest west flowing and seventh largest river in India, covers a large area of Madhya Pradesh state besides some area of Maharashtra state and Gujarat state before entering into the Gulf of Cambey, the Arabian sea. Narmada basin lies between 72˚ 32' E to 82˚ 45' E and 21˚ 20' N to 23˚ 45' N. The total catchment area is 98796 Sq. Km. The observations of daily streamflow and rainfall for 11 years (1987 to 1997) at the first station Mandaleshwar which lies on Narmda river were available from Central Water Commission Bhopal division [5]. India receives rainfall almost for 4 months all over the country. The Narmada catchment receives the rainfall starting from late June continuing till early October.

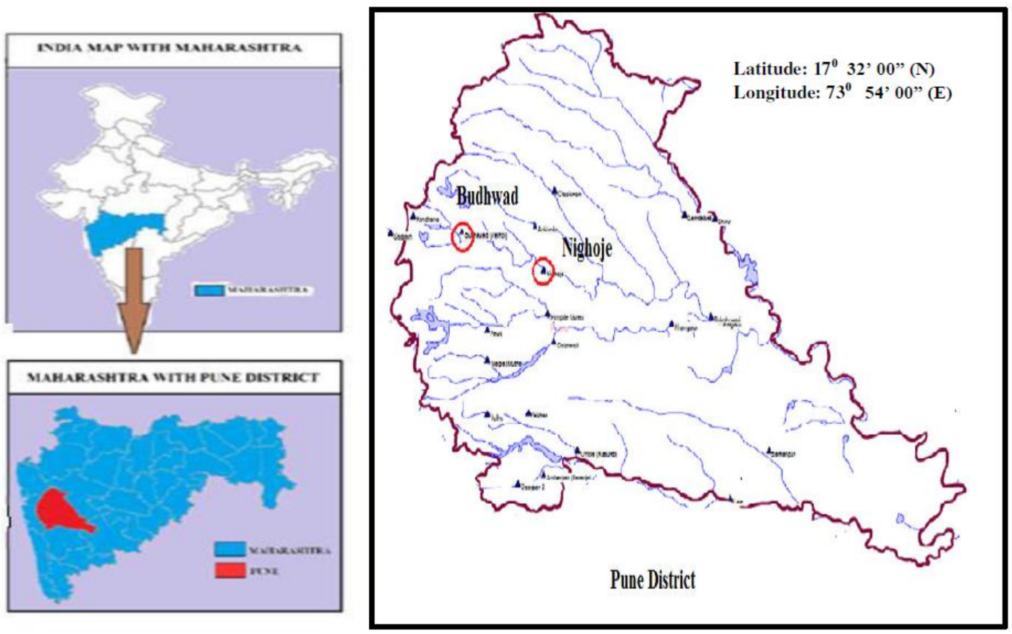
Krishna Basin is India's fourth largest river basin, which covers 2, 58, 948 Sq. Km. of Southern India. Krishna river originates in the Western Ghats at an elevation of about 1337 m just North of Mahabaleshwar in Maharashtra, India about 64 Km from Arabian sea and flows for about 1400 Km and outfalls into the Bay of Bengal traversing three states Karnataka (1,13,271 Sq. Km), Andhra Pradesh (76,252 Sq. Km), Maharashtra (69,425 Sq. Km). The second rainguage and discharge measurement station Nighoje is on Bhima tributary and Indrayani stream of Krishna river basin in Pune district of Maharashtra state of India. Total 13 years of data (1995 to 2007) was used for developing the models. The third rainguage and discharge measurement station Budhwad is on Bhima tributary and Kundalika stream of Krishna river basin in Pune district of Maharashtra state of India. Total 14 years of data (1994 to 2007) was used for developing the models at Budhwad. Both the locations receive rainfall in the monsoon months starting from early June continuing till early October. The Data for Nighoje and Budhwad was collected by Hydrology Project Nasik [6]. The statistical parameters of the data are as shown in Table 1 and Table 2 which indicate that there is a lot of variation in the observed values of rainfall and discharge quantities in Narmda and Krishna river catchments. Figure 1 shows the study area.

3. Fundamentals of support vector machine

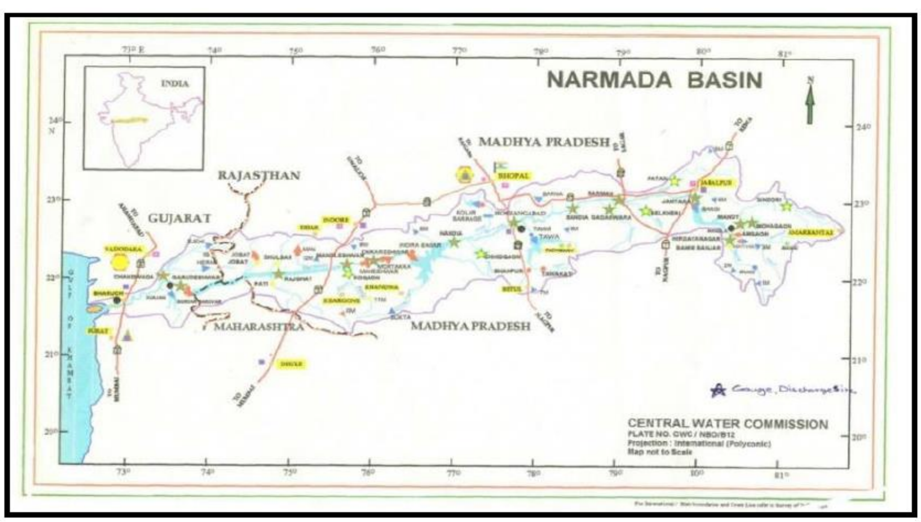
Support vector machines, commonly used for classification and regression purposes is a method of supervised learning. An SVM constructs a separating hyperplane between the classes in the n-dimensional space of inputs. A special property of SVM is that they minimize the regression error and maximize the geometric margin making them maximum margin classifiers. This is one of the most advantageous features of SVM compared to Artificial Neural Network (ANN) [7]. Readers are referred to [8,9] for details of SVM.

3.1. Support vector regression

Support Vector Regression (SVR) is a nonlinear regression method based on Support Vector Machines (SVM). The basic idea behind support vector regression is to map the data into a higher dimensional feature space using nonlinear mapping and then to solve a linear regression problem in the new space. Support Vector regression has gained popularity due to many attractive features, one among them being promising empirical performance.The formulation embodies the Structural Risk Minimization (SRM) principle, which is superior to the Empirical Risk Minimization (ERM) principle, employed by conventional neural networks. The non-linear mapping is achieved through the application of Kernel functions. In the present work a support vector machine learning approach known as Least square-support vector machine (LS-SVM), which makes use of different kernel functions such as Linear, Polynomial, Gaussian Radial Basis Function, Exponential Radial Basis Function, etc is employed. The LSSVM considers equality constraints for the classification problem as against the inequality as in standard SVM with a formulation in the least squares sense because of which the solution follows directly from solving a set of linear equations, rather than quadratic programming. While in classical SVM's many support values are zero (nonzero values correspond to support vectors), at least squares SVM's the support values are proportional to the errors. For details of SVR readers are referred to [10] and for details of LS-SVM readers are referred to [11].



a Map for Budhwad and Nighoje, Maharashtra, India



b Map for Mandaleshwar, Madhya Pradesh, India

Fig. 1. Study Area.

3.2. Kernel function

Kernel function represents the inner product of one space into another space. The training set is linearly separable in the feature space rather than the input space. This is called the "Kernel trick". This is done using Mercer's theorem [8] which states that any unknown, symmetric positive definite kernel function K (x,y) can be expressed as a dot product in a high- dimensional space. More specifically if the argument to the kernel is in a 'measurable space x' and if the kernel is positive semi-definite then,

$$\sum_{i,j} k(x_i, x_j) c_i c_j \geq 0 \tag{1}$$

for any finite subset $(x_1,...x_n)$ of x and subset $\{c_1,...c_n\}$ of objects (typically real numbers) there exists a function Φ(x) whose range is in an inner product space of possibly higher dimension such that

$$(x,y) = \Phi(x). \Phi(y) \tag{2}$$

The kernel trick transforms any algorithm that solely depends on the dot product between two vectors. Kernel function enables operations to be performed in input space. Hence there is no need to evaluate inner products in the feature space. Computations depend on the number of training patterns. The large training set is required for a high- dimensional problem. The most important benefit of using kernel is that the dimensionality of the feature space does not affect the computations. Some commonly used kernels in SVM are Linear, Polynomial, Gaussian Radial Basis Function, Exponential Radial Basis Function, Multi-Layer Perceptron, Fourier series, B Splines, and Splines. In the present work radial basis function kernel (RBF), linear kernel and polynomial kernel are used for calibration of models. For details of the kernel, readers are referred to [12].

3.3. Linear kernel

The Linear kernel is the simplest kernel function. It is given by the inner product (x,y).

$$< X, X_i > \tag{3}$$

Where X_1 and X_2 are two vectors

3.4. Polynomial kernel

The Polynomial kernel is a non-stationary kernel. Polynomial kernels are well suited for problems where all the training data is normalized.

$$(< X, X_i > +1)^d \tag{4}$$

Where, d- degree (order)

3.5. Gaussian kernel

The Gaussian kernel is an example of radial basis function kernel.

$$\exp(-\|X - X_i\|^2 / 2\sigma^2) \quad (5)$$

The adjustable parameter sigma plays a major role in the performance of the Gaussian kernel and should be carefully tuned to the problem at hand. σ controls the width of the Gaussian function. If overestimated, the exponential will behave almost linearly, and the higher-dimensional projection will start to lose its non-linear prowess. On the other hand, if underestimated, the function will lack regularization, and the decision boundary will be highly sensitive to noise in training data. For nonlinear regression, the most common kernel method used is probably the RBF kernel method. Readers are referred to [12,13] for details about SVR.

3.6. Applications of support vector regression in streamflow forecasting

Dibike et al. (2001) employed SVM for land use classification and rainfall-runoff prediction using a polynomial and RBF kernel. Results showed better performance than ANN-derived models, with the RBF kernel also performing better than the polynomial one [9]. SVMs were explored in flood forecasting by [14], with focus on the identification of a suitable model structure and its relevant parameters for rainfall-runoff modeling. The paper further explored the relationships among various model structures, kernel functions, scaling factor, model parameters and composition of input vectors. [15] used SVM for forecasting streamflow at multi-time scales in an ungauged river basin in Utah, USA.Method of trial and error was used for selection of optimum inputs. An RBF kernel was used for model preparation with the SVM, while a cross-validation approach was used for estimating the SVM parameters. [16] demonstrated the capability of SVMs to predict long-term flow discharges while using a hydrological time series with nonlinear features. [17] used SVR for real-time flood stage forecasting. [10] proposed a distributed SVR (D-SVR) in which a linear regression (LR) and two-step GA algorithm was used alongside Gaussian RBF kernel to find the optimal model parameters. One-day lead stream flow of Bakhtiyari River in Iran was predicted using SVM and the local climate and rainfall data [18]. The results were compared with those of ANN and ANN integrated with genetic algorithms (ANN-GA) models. The authors found that SVM results were at par or sometimes even better than ANN and ANN-GA models. [19] developed SVM model to predict the next monthly flow as a function of 18 input variables (initially) including monthly rainfall (R), discharge (Q), sun radiation (Rad), and temperature {as minimum (Tmin), maximum (Tmax) and average (Tave)} with three temporal delays belong to t, t-1, and t-2. Subsequently, principal component analysis (PCA), Gamma test (GT), and forward selection (FS) techniques were used to reduce the number of input variables to 5 and fed to SVM.

The daily stream flow and suspended sediment concentration at two stations on the Eel River in California were modeled using ANN and LSSVM by [20]. Comparison of results showed that the LSSVM model was able to produce better results than the ANN models. [21] explored the potential of LS-SVR for daily stream flow forecasting in Narmada river basin up to Sandia gauging station and Mahanadi river basin up to Basantpur gauging station in India. They reported that the peak stream flow values were not captured with reasonable accuracy. All the above works showed concern about the selection of Kernel and hyper-parameters.

Sahraei et al. [22] used least square support vector regression (LSSVR) and Regression Tree (RT) for prediction of river flow in Kashkan watershed of Iran. The inputs were precipitation and discharge values of one and two previous days with present discharge as output. It was found that the LSSVR model had better performance than RT models.

Kalteh [23] used Wavelet Genetic Algorithm-Support Vector Regression (wavelet GA-SVR) and regular Genetic Algorithm-Support Vector Regression (GA-SVR) models for forecasting monthly flow on two rivers in northern Iran. The genetic algorithm was applied for selecting the optimal parameters of the support vector regression (SVR) models. It was found that the wavelet GA-SVR models were able to provide more accurate forecasting results than the regular GA-SVR models. The performance of LSSVM was improved by data preprocessing using singular spectrum analysis (SSA) and discrete wavelet analysis (DWA) by [24,25] at Kharjeguil and Ponel stations from Northern Iran while forecasting monthly streamflow data. Forecasting and estimation of monthly streamflow were done by [26] at 2 stations in Turkey using least square support vector regression (LSSVR) and adaptive neuro-fuzzy embedded fuzzy c-means clustering (ANFIS-FCM). The LSSVR was found to be better than the ANFIS-FCM.

In the present work, a comparison of three input selection methods and four different data combinations with three kernels for one day ahead streamflow forecasting using support Vector Regression (SVR) is done. It is the first work of its kind where in three input selection methods along with different data combinations and three kernels are employed.

4. Model formulation

Daily rainfall and discharge data were available at all the three locations for the months of June to October for the years mentioned in preceding section 2. After examining the data, it was found that the average discharge and rainfall values for monsoon months of July to October were differing considerably (Table 1 and 2). Therefore it was decided to develop separate monthly stream flow models for monsoon months as India experiences separate monsoon season and rainfall and discharge show considerable variations in each of these months. Two types of models, separate monthly and for 4 or 5 months together were prepared (June to September or June to October) to judge the model performance in terms of accuracy of prediction. The next task was a determination of antecedent discharges and rainfall to be used as inputs for predicting discharge one day in advance. This was achieved by three different methods namely trial and error, correlation analysis and Average Mutual Information (AMI).

4.1. Trial and error

Method of the trial is a simple method which does not assume linearity. In trial and error, previous values of independent variables (in this case rainfall and discharge) are added one by one till the best possible results are achieved. In the present work, models are named as ip1, ip2, ip3 and so on till ip10. For a monthly model, it is started with one value of current day discharge as input to predict the discharge of the next day (ip1). To this value of discharge one value of current day, rainfall is added, with discharge on the next day is maintained as output (ip2). For further models alternate one lag (previous value) of discharge and one lag of rainfall are added to previous inputs. For models named with odd numbers, one previous value of discharge is added for every trial and for models named with even numbers one previous value of rainfall is added for each trial. Likewise, till ip10 total 5 previous values of discharges and rainfall are used. It was found that the model performance does not change with any further addition of previous rainfall or discharge values. Model nomenclature and input details in the method of trial and error are shown in Table 3. An example of 5 previous values each of rainfall and discharge (ip10) to predict runoff one day in advance in the functional form is shown below,

$$Q_{t+1} = f(R_{t-4}, R_{t-3}, R_{t-2}, R_{t-1}, R_t, Q_{t-4}, Q_{t-3}, Q_{t-2}, Q_{t-1}, Q_t) \tag{6}$$

Table 1
Statistical Analysis of Discharge at Mandaleshwar, Nighoje, and Budhwad.

Mandaleshwar						
Month	**Mean (m^3/s)**	**Standard Deviation (m^3/s)**	**Kurtosis**	**Skewness**	**Minimum (m^3/s)**	**Maximum (m^3/s)**
July	2349.25	4267.52	19.24	3.89	43.21	36045
August	4084.3	4096.82	7.41	2.38	66.17	27093
Sept	2844.58	3369.69	39.92	5.11	317.2	35450
Oct	682.58	741.66	20.54	4.09	190.8	5848
4 Monthly	2486.17	3632.2	21.41	3.85	43.21	36045
Nighoje						
June	44.45	82.22	25.54	4.34	0.27	678.16
July	96.67	133.4	23.3	3.8	0.26	1299.62
August	106.92	169.1	57.01	6.2	1.97	2110.92
September	36.19	46.46	22.01	3.8	1.18	446.09
October	14.85	21.68	61.27	6.17	0.36	267.43
5 Monthly	64.31	117.21	78.88	6.76	0.26	2110.92
Budhwad						
June	9.5	16.64	11.26	3.18	0.58	97.16
July	23.11	34.05	9.28	2.75	0.05	220.13
August	22.19	30.82	14.69	3.35	0.69	259.03
September	9.25	15.24	28.54	4.54	0.5	146.71
October	2.77	3.13	8.09	2.64	0.21	18.99
5 Monthly	14.59	25.57	20.39	3.93	0	259.03

Table 2
Statistical Analysis of Rainfall at Mandaleshwar, Nighoje and Budhwad.

Month	Mean (mm)	Standard Deviation (mm)	Kurtosis	Skewness	Minimum (mm)	Maximum (mm)
Mandaleshwar						
July	9.14	24.36	20.06	4.25	0	187.6
August	8.07	16.72	11.25	3.16	0	112
Sept	4.54	13.27	22.99	4.34	0	112.6
Oct	0.85	4.67	47.70	6.73	0	43.1
4 Monthly	5.66	16.67	32.41	5.07	0	187.60
Nighoje						
June	10.28	17.93	8.23	2.74	0	102.00
July	6.77	13.22	12.86	3.28	0	94
August	6.16	14.16	45.37	5.72	0	162.00
September	4.75	11.14	17.95	3.81	0	92.20
October	3.34	10.91	63.81	6.65	0	131.60
5 Monthly	5.81	13.23	28.23	4.46	0	162
Budhwad						
June	37.50	46.00	4.67	2.02	0	250
July	35.11	44.96	11.02	2.69	0	365.60
August	23.08	32.17	15.46	3.35	0	273
September	9.52	17.25	21.52	3.75	0	160
October	4.44	10.61	10.95	3.19	0	63.60
5 Monthly	20.93	34.11	17.04	3.40	0	365.60

Table 3
Model name and input used in trial and error.

Model Name	Inputs
ip1	1 Previous Discharge
ip2	1 previous Discharge and 1 previous rainfall
ip3	2 previous Discharge and 1 previous rainfall
ip4	2 previous Discharge and 2 previous rainfall
ip5	3 previous Discharge and 2 previous rainfall
ip6	3 previous Discharge and 3 previous rainfall
ip7	4 previous Discharge and 3 previous rainfall
ip8	4 previous Discharge and 4 previous rainfall
ip9	5 previous Discharge and 4 previous rainfall
ip10	5 previous Discharge and 5 previous rainfall

4.2. Correlation analysis

The degree of dependence between the variables can be assessed through the correlation analysis. For same variables (discharge as input for discharge) auto-correlation analysis yields the influence of past values on the future values of the time series. For two different variables (rainfall and discharge) this is done through cross-correlation analysis which manifests the influence of previous values of rainfall on the discharge. In the present work 50% value of maximum autocorrelation and cross-correlation is considered for deciding lags and including them as inputs. For example from figure 2 to predict discharge Q_{t+1}discharge Q_t and discharge of Q_{t-1}, as well as rainfall Rt and Rt-1, are selected as inputs.

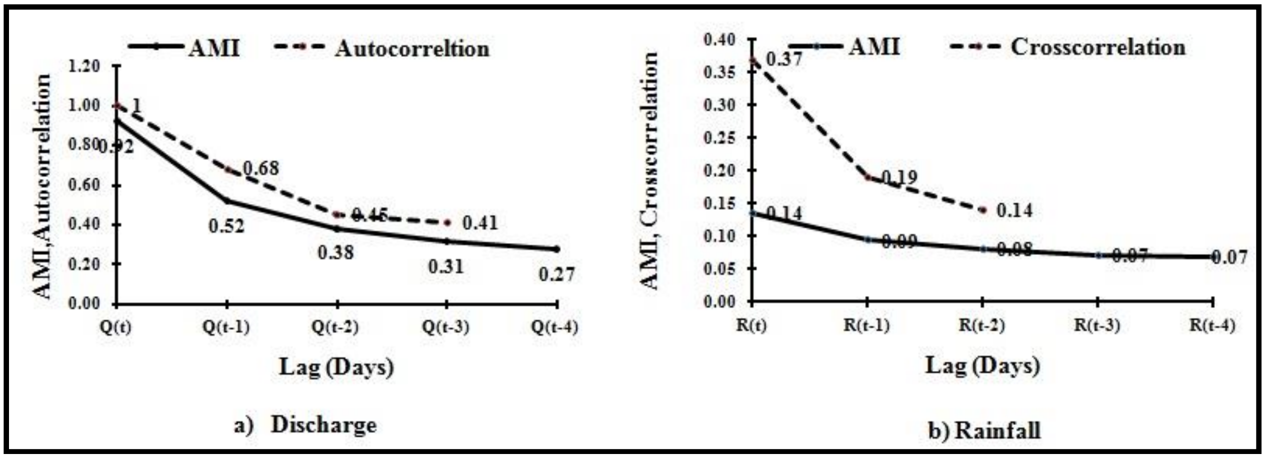


Fig. 2. Typical Correlogram and AMI for input selection (4 monthly Mandaleshwar model).

4.3. Average mutual information (AMI)

The correlation analysis is a measure of linear dependence only. It is a well-known fact that rainfall-runoff process is a highly nonlinear complex process. In view of this, another input selection method based upon joint probability densities of rainfall and runoff is also tried. The Average Mutual Information (AMI) measures the dependence between the two random variables (Zamini et al. 2008) [27].

$$AMI(A,B) = \sum P_{A,B}(a_i,b_j) * \log 2 \left[\frac{P_{A,B}(a_i,b_j)}{P_A(a_i)P_B(b_j)} \right] \tag{7}$$

Where a_i and b_j = i_{th} or j_{th} bi-variate sample pair

n = sample size

$P_A(a_i)$, $P_B(b_j)$ = Uni-variate probability densities

$P_{A,B}(a_i, b_j)$ = Joint probability densities

AMI mainly measures the information that A and B share. It measures how much knowledge about one of these variables reduces our uncertainty about the other variable.

In case of AMI antecedent values of rainfall and discharge are decided from the highest value of AMI and the values which are 50% of highest values [27]. For example to predict discharge Q_{t+1} discharge Q_t and Q_{t-1} along with rainfall R_t, R_{t-1}, R_{t-2}, R_{t-3}, $R_{t-4}$are selected as inputs from figure 2.

It has been shown that unlike ANNs, SVR can work better with much less training data [28]. In view of this, four different combinations of data division are tried. Calibration of the model using first 70% data and testing for the last 30 % of data was the first option tried. The second attempt was made using first 30 % data for calibration and last 70 % data for testing. In the next attempt, calibration was done for the last 70% data and testing for first 30 % data. Finally, last 30% data was used for calibration and first 70 % data for testing.

At Mandaleshwar for separate monthly models with the method of trial and error along with one kernel for each model four different data combinations (as mentioned above) were used and models were developed from ip1 till ip10. Thus total 40 models were developed for each month. A similar pattern was followed for kernel two and kernel three. So for each month total, 120 models were developed. So for all three kernels together for monthly and 4 monthly models total 600 models with trial and error were developed. On similar lines with method of AMI and with one kernel for each month 4 models were developed. Thus for monthly and 4 monthly total 20 models with one kernel and 60 models with all three kernels together were developed with AMI. The same suite was followed for input selection by correlation analysis with kernel type 1, so for each month total, 4 models were developed, which resulted in the formation of total 20 models for separate months and 4 monthly models (June to September together). Thus total 60 models were developed for three kernels. The total number of models developed is given below based upon the above discussion.

At Mandaleshwar for four months of July, August, September, October total 600 models were prepared for a method of trial and error, 60 models for AMI and 60 models for correlation analysis. At Nighoje for five months of June, July, August, September and October total 240 models with trial and error and 24 models with AMI were prepared. At Budhwad total 240 models with trial and error and 24 models with AMI were prepared. For all stations thus total 1248 models were prepared. It can be seen from the table of statistical analysis (table 1 and 2) that all the selected stations have a large variation in rainfall and discharge values. So to analyze SVR performance with different rainfall and discharge combinations these many model formulations were done.

Results were assessed by plotting the scatter plot between observed and predicted stream flow in testing and by drawing hydrograph of observed and predicted streamflow. Though the coefficient of correlation between the observed and predicted streamflow is generally calculated to judge the accuracy of model prediction, it is not considered in the present work owing to its limitations as mentioned by [29]. Instead one absolute error measure, Root Mean Squared Error (RMSE), one relative error measure Mean Absolute Relative Error (MARE) and one non dimensional error measure Coefficient of Efficiency (CE) were used as suggested by [29]. Need for more than one model assessment technique has also been emphasized by [30]. For details of error calculation readers are referred to [30].

5. Results and discussion

All the models were tested with unseen data and results were compared by plotting to scatter plots, hydrograph as well as three error measures as mentioned in the previous section. Primarily RMSE was used to compare results of different models followed by CE and MARE. Results with bold letters indicate the best model. Consolidated results are shown in Table 4 to 16 at the end. Results of Mandaleshwar are discussed first. It may be noted that the results discussed below are the best in a respective category which is compared further to nominate the best model amongst all possibilities.

5.1. Mandaleshwar

For the month of July, model with one previous discharge and rainfall as inputs by trial and error method and calibrated with last 70 % values (ip2) and RBF kernel shows RMSE as 1366.48 m^3/s (model 8), while two previous discharge and one rainfall values as inputs by AMI with RBF kernel and calibrated using last 30 % data shows RMSE of 55.88 m^3/s (model 603) which is very low. Model developed with two previous discharges and one previous rainfall as inputs by correlation analysis and calibrated using last 70 % data and RBF kernel shows RMSE of 1414.68 m^3/s (model 664), which clearly indicates superiority of AMI over trial and error and correlation method for the month of July from the point of view of input selection. The model developed using a linear kernel with one previous discharge and calibrated with the last 70 % data (trial and error method) shows RMSE equal to 1365.12 m^3/s (model 44). Model with two previous discharges and four rainfall values as inputs (AMI method of input selection) and calibrated with last 70 % data yields RMSE equal to 2064.74 m^3/s (model 624). The further model developed with two previous discharges and one previous rainfall as inputs byCorrelation analysis shows RMSE equal to 1460.6 m^3/s (model 684). The model developed with polynomial kernel and with one previous discharge as input and calibrated with last 70 % data (trial and error) shows RMSE equal to 1365.53 m^3/s (model 84). While model developed with one previous discharge and two rainfall values as inputs (AMI) and calibrated with last 70 % data shows RMSE equal to 2064.74 m^3/s (model 644). The model developed using two previous discharges and one previous rainfall as inputs (correlation analysis) and calibrated with last 70 % data shows RMSE equal to 1459.8 m^3/s (model 704). It can be seen that values of error measures for polynomial kernel and linear kernel are very similar. This can be attributed to the degree of polynomial being '1' in polynomial kernel making it same as the Linear Kernel. When it was tried to calibrate the models with a higher order of polynomials the results were poor. It can also be seen that RBF kernel exhibited the best performance out of all the three kernels (model 603). As evident from the results, AMI seems to be the best among the three input selection methods. Refer table 4 for results of July.

For the models developed for the month of August the RMSE values by using method of trial and error for input selection with RBF kernel (calibrated with the last 70 % data), Linear kernel (calibrated with the last 70 % data) and Polynomial Kernel (calibrated with the last 70 % data) are 2571.14 m^3/s (model 136), 2574.43 m^3/s (model 172) and 2574.14 m^3/s (model 212) respectively. Input selection using AMI along with RBF kernel and calibration with last 70 % data yields RMSE of 2426.3 m^3/s (model 608) while Linear kernel and calibration with last 70 % data shows RMSE of 2454.1 m^3/s (model 628), and Polynomial kernel with calibration using the last 70 % shows RMSE of 2453.6 m^3/s (model 648), respectively. The model developed using correlation analysis as input selection method shows RMSE equal to 2576.64 m^3/s (model 668) with RBF kernel and last 70 % of data for calibration. Model calibrated with linear kernel and last 70 % data for calibration shows RMSE of 2574.4 m^3/s (model 688), while calibration with Polynomial kernel and last 70 % data shows RMSE of 2574.14 m^3/s (model 708). Thus as evident from these results, AMI is again working better amongst the three input selection methods along with RBF kernel owing to its lowest RMSE. Results of August are shown in Table 5.

For September, the model developed using the method of trial and error for input selection and, calibration with first 70 % data and RBF kernel gives RMSE of 994.92 m^3/s (model 253), while Linear kernel with first 70 % data calibration yields RMSE of 1099.04 m^3/s (model 285). The model developed using Polynomial kernel and first 70 % data for calibration shows RMSE equal to 1096.91 m^3/s (model no. 325). The model developed using the method of AMI for input selection with RBF kernel shows RMSE of 1215.8 m^3/s (model 612) for last 70 % calibration of data, while Linear kernel shows RMSE as 1323.5 m^3/s (model 632) for first 70 % calibration of data. For model calibrated using Polynomial kernel and calibration with first 70% data shows RMSE equal to 1323.6 m^3/s (model 652). The model developed using input selection method of Correlation analysis shows RMSE equal to 1066.72 m^3/s (model 669) for RBF kernel with first 70 % data used for calibration. Model calibrated with linear kernel and first 70 % of data shows RMSE of 1171 m^3/s (model 689). Similarly, model calibrated with Polynomial kernel and first 70 % of data shows RMSE equal to 1162.3 m^3/s (model 709). Thus for the month of September model developed using trial and error method of input selection with RBF kernel is the best owing to its lowest RMSE value. Results of September are shown in Table 6.

For the month of October, a model with the method of trial and error for input selection and calibration with RBF kernel and the first 70 % data shows RMSE of 122.89 m^3/s (model 373), while calibration with first 70 % data and Linear kernel shows RMSE of 121.67 m^3/s (model 413). For model calibrated with first 70 % data and polynomial kernel RMSE is equal to 121.67 m^3/s (model 453). The method of AMI for input selection exhibits RMSE of 194 m^3/s (model 613), 125.9 m^3/s (model 633), 125.8 m^3/s (model 653) for model calibrated with RBF kernel and the first 70 % data, Linear kernel and the first 70 % data and Polynomial kernel with the first 70 % respectively. When correlation analysis was used as input selection method with RBF kernel and calibration with the first 70 % data RMSE of 134.1 m^3/s was obtained (model 673). For linear kernel and calibration with the first 70 %, RMSE was 123.9 m^3/s (model 693) while calibration with polynomial kernel and the first 70 % data RMSE was 123.9 m^3/s (model 713). Here once again method of trial and error along with RBF kernel is the best combination. Refer table 7 for results of October models.

Table 4
July Results of Mandaleshwar with Trial and Error.

Model Name	Training percentage	Model No.	RBF Kernel			Model No.	LINEAR Kernel			Model No.	POLYNOMIAL Kernel		
			RMSE	CE	MARE		RMSE	CE	MARE		RMSE	CE	MARE
ip1	First 70	1	4627.82	0.38	1.44	41	4845.42	0.32	1.30	81	4845.42	0.32	1.30
	First 30	2	4251.63	0.26	2.20	42	3696.92	0.44	2.09	82	3700.48	0.44	2.10
	Last 30	3	2326.26	0.51	4.11	43	2202.36	0.56	3.40	83	2202.36	0.56	3.40
	Last 70	4	1380.68	0.26	2.10	44	1365.12	0.28	1.94	84	1365.53	0.28	1.95
ip2	First 70	5	4615.83	0.38	1.39	45	4823.91	0.32	1.30	85	4800.44	0.32	1.29
	First 30	6	4253.01	0.26	2.12	46	3680.02	0.44	2.07	86	3680.02	0.44	2.07
	Last 30	7	2308.80	0.52	4.02	47	2204.99	0.56	3.32	87	2203.16	0.56	3.35
	Last 70	8	1366.48	0.28	1.92	48	1370.20	0.27	1.97	88	1377.07	0.27	1.98
ip3	First 70	9	4541.90	0.40	1.50	49	4812.25	0.33	1.50	89	4833.98	0.32	1.46
	First 30	10	4471.21	0.18	1.98	50	3766.33	0.42	2.03	90	3766.33	0.42	2.03
	Last 30	11	2261.15	0.54	3.88	51	2173.07	0.58	3.63	91	2178.11	0.58	3.65
	Last 70	12	1414.68	0.22	2.02	52	1460.60	0.18	2.18	92	1459.80	0.18	2.19
ip4	First 70	13	4551.12	0.40	1.42	53	4804.09	0.33	1.46	93	4804.09	0.33	1.46
	First 30	14	4475.85	0.18	1.93	54	3752.38	0.42	2.03	94	3752.38	0.42	2.03
	Last 30	15	2243.12	0.55	3.71	55	2261.88	0.55	3.99	95	2249.39	0.55	3.91
	Last 70	16	1437.84	0.20	1.85	56	1489.48	0.15	2.31	96	1489.48	0.15	2.31
ip5	First 70	17	4578.09	0.35	1.57	57	4870.84	0.27	1.48	97	4871.64	0.27	1.48
	First 30	18	4448.17	0.19	1.98	58	3834.26	0.40	2.03	98	3834.26	0.40	2.03
	Last 30	19	2373.14	0.54	3.79	59	2299.27	0.57	3.47	99	2297.92	0.57	3.49
	Last 70	20	1447.88	0.19	1.95	60	1420.33	0.21	2.03	100	1427.58	0.21	2.05
ip6	First 70	21	4553.78	0.36	1.49	61	4821.57	0.28	1.53	101	4821.57	0.28	1.53
	First 30	22	4471.72	0.18	1.93	62	3820.80	0.40	2.02	102	3827.09	0.40	2.03
	Last 30	23	2366.23	0.54	3.62	63	2379.06	0.54	3.87	103	2347.23	0.56	3.77
	Last 70	24	1471.58	0.17	1.80	64	1445.50	0.19	2.19	104	1443.01	0.20	2.20
ip7	First 70	25	4626.36	0.34	1.59	65	4926.89	0.26	1.64	105	4926.89	0.26	1.64
	First 30	26	4487.79	0.18	1.98	66	3825.77	0.40	2.07	106	3825.77	0.40	2.07
	Last 30	27	2376.32	0.54	3.75	67	2316.80	0.57	3.58	107	2310.14	0.57	3.58
	Last 70	28	1477.71	0.16	1.89	68	1439.50	0.19	2.13	108	1430.78	0.19	2.12
ip8	First 70	29	4618.05	0.34	1.51	69	4899.53	0.27	1.62	109	4899.53	0.27	1.62
	First 30	30	4515.58	0.17	1.92	70	3814.11	0.41	2.06	110	3814.11	0.41	2.06
	Last 30	31	2371.30	0.54	3.56	71	2420.81	0.53	4.06	111	2382.20	0.55	3.99
	Last 70	32	1508.34	0.12	1.73	72	1479.15	0.15	2.32	112	1473.68	0.16	2.32
ip9	First 70	33	4641.72	0.34	1.45	73	4929.06	0.26	1.66	113	4929.06	0.26	1.66
	First 30	34	4589.07	0.15	1.97	74	3832.16	0.40	2.03	114	3832.16	0.40	2.03
	Last 30	35	2385.67	0.54	3.77	75	2388.97	0.54	3.48	115	2370.24	0.55	3.49
	Last 70	36	1419.69	0.21	1.86	76	1422.40	0.20	2.08	116	1428.36	0.20	2.11
ip10	First 70	37	4665.07	0.34	1.39	77	4902.71	0.27	1.65	117	4902.71	0.27	1.65
	First 30	38	3821.82	0.41	2.02	78	3821.82	0.41	2.02	118	3821.82	0.41	2.02
	Last 30	39	2388.47	0.54	3.57	79	2473.77	0.52	4.02	119	2426.60	0.53	3.91
	Last 70	40	1499.18	0.13	1.69	80	1470.46	0.16	2.30	120	1465.11	0.17	2.30

Table 5
August Results of Mandaleshwar With Trial and Error

Model Name	Training percentage	Model No.	RBF Kernel			Model No.	LINEAR Kernel			Model No.	POLYNOMIAL Kernel		
			RMSE	CE	MARE		RMSE	CE	MARE		RMSE	CE	MARE
ip1	First 70	121	2829.33	0.41	0.60	161	2863.93	0.39	0.56	201	2863.93	0.39	0.56
	First 30	122	3005.23	0.49	0.45	162	3014.88	0.49	0.44	202	3014.91	0.49	0.44
	Last 30	123	2931.37	0.52	1.05	163	2933.26	0.52	1.14	203	2933.91	0.52	1.14
	Last 70	124	2595.56	0.50	2.27	164	2586.64	0.51	2.12	204	2586.69	0.51	2.12
ip2	First 70	125	2858.78	0.39	0.60	165	2868.54	0.39	0.56	205	2868.54	0.39	0.56
	First 30	126	3061.99	0.47	0.43	166	3085.05	0.47	0.42	206	3085.15	0.47	0.42
	Last 30	127	3067.01	0.48	1.33	167	2942.77	0.52	1.17	207	2945.60	0.52	1.18
	Last 70	128	2607.90	0.50	2.26	168	2636.87	0.49	2.09	208	2635.79	0.49	2.11
ip3	First 70	129	2842.97	0.40	0.58	169	2971.23	0.35	0.60	209	2966.19	0.35	0.60
	First 30	130	2945.02	0.52	0.45	170	2974.33	0.51	0.44	210	2974.77	0.76	0.44
	Last 30	131	3048.98	0.48	1.17	171	2935.00	0.52	1.06	211	2941.11	0.52	1.07
	Last 70	132	2576.64	0.51	1.93	172	2574.43	0.51	2.15	212	2574.14	0.51	2.16
ip4	First 70	133	2721.30	0.71	0.59	173	2705.20	0.46	0.56	213	2705.30	0.46	0.56
	First 30	134	2840.90	0.78	0.40	174	2840.90	0.55	0.40	214	2840.90	0.55	0.40
	Last 30	135	2864.20	0.78	1.17	175	2628.60	0.62	0.94	215	2622.10	0.62	0.93
	Last 70	136	2426.30	0.77	2.11	176	2454.10	0.56	1.93	216	2453.60	0.56	1.95
ip5	First 70	137	2855.45	0.40	0.59	177	2962.58	0.38	0.60	217	2957.98	0.36	0.60
	First 30	138	2953.37	0.51	0.45	178	2983.40	0.50	0.44	218	2983.40	0.50	0.44
	Last 30	139	2957.19	0.51	0.93	179	2944.23	0.52	0.93	219	2944.23	0.52	0.93
	Last 70	140	2596.06	0.50	1.37	180	2616.85	0.49	1.80	220	2613.96	0.49	1.82
ip6	First 70	141	2959.56	0.36	0.60	181	2921.80	0.37	0.59	221	2947.66	0.36	0.59
	First 30	142	3031.52	0.49	0.43	182	3089.82	0.47	0.43	222	3089.82	0.47	0.43
	Last 30	143	3112.44	0.46	1.08	183	2958.53	0.51	0.97	223	2958.53	0.51	0.97
	Last 70	144	2583.43	0.50	1.66	184	2655.15	0.48	1.81	224	2650.61	0.48	1.82
ip7	First 70	145	2834.08	0.41	0.59	185	2948.40	0.37	0.60	225	2945.04	0.37	0.60
	First 30	146	2986.50	0.50	0.46	186	3016.96	0.49	0.45	226	3016.96	0.49	0.45
	Last 30	147	2951.52	0.51	0.92	187	2963.98	0.51	0.98	227	2963.98	0.51	0.98
	Last 70	148	2604.68	0.49	1.59	188	2642.00	0.48	1.85	228	2640.41	0.48	1.86
ip8	First 70	149	2909.27	0.38	0.59	189	2949.66	0.37	0.60	229	2949.66	0.37	0.60
	First 30	150	3047.62	0.48	0.44	190	3105.35	0.46	0.44	230	3105.35	0.46	0.44
	Last 30	151	3062.34	0.48	1.06	191	2975.66	0.51	1.01	231	2975.66	0.51	1.01
	Last 70	152	2592.59	0.50	1.63	192	2673.14	0.46	1.86	232	2667.33	0.47	1.87
ip9	First 70	153	2816.41	0.42	0.59	193	2964.76	0.36	0.60	233	2960.87	0.36	0.60
	First 30	154	3067.94	0.48	0.47	194	3147.99	0.45	0.47	234	3147.87	0.45	0.47
	Last 30	155	2969.54	0.51	0.86	195	3026.59	0.49	1.00	235	3026.59	0.49	1.00
	Last 70	156	2620.94	0.48	1.54	196	2649.62	0.47	1.80	236	2645.94	0.47	1.81
ip10	First 70	157	2893.02	0.38	0.60	197	2967.04	0.36	0.60	237	2967.04	0.36	0.60
	First 30	158	3167.35	0.44	0.46	198	3271.69	0.41	0.46	238	3271.69	0.41	0.46
	Last 30	159	3005.49	0.50	0.84	199	3032.03	0.49	1.03	239	3032.03	0.49	1.03
	Last 70	160	2608.29	0.49	1.53	200	2681.63	0.46	1.81	240	2676.59	0.46	1.82

Table 6
September Results of Mandaleshwar With Trial and Error.

Model Name	Training percentage	Model No.	RBF Kernel			Model No.	LINEAR Kernel			Model No.	POLYNOMIAL Kernel		
			RMSE	CE	MARE		RMSE	CE	MARE		RMSE	CE	MARE
ip1	First 70	241	1173.88	0.50	0.47	281	1156.94	0.50	0.45	321	1169.08	0.50	0.46
	First 30	242	2837.54	0.45	0.41	282	2531.16	0.56	0.34	322	2531.76	0.56	0.34
	Last 30	243	2940.43	0.41	0.45	283	2549.29	0.56	0.37	323	2549.29	0.56	0.37
	Last 70	244	1222.93	0.55	0.57	284	1217.60	0.55	0.57	324	1217.60	0.55	0.57
ip2	First 70	245	1028.36	0.62	0.52	285	1099.04	0.56	0.47	325	1096.91	0.56	0.48
	First 30	246	2965.99	0.39	0.41	286	2527.89	0.56	0.34	326	2527.96	0.56	0.34
	Last 30	247	3010.64	0.38	0.46	287	2605.56	0.54	0.39	327	2605.56	0.54	0.39
	Last 70	248	1259.72	0.52	0.62	288	1248.55	0.53	0.59	328	1248.55	0.53	0.59
ip3	First 70	249	1178.41	0.50	0.42	289	1312.40	0.38	0.56	329	1312.40	0.38	0.56
	First 30	250	2932.01	0.41	0.42	290	2470.34	0.58	0.35	330	2470.72	0.58	0.35
	Last 30	251	3027.48	0.38	0.49	291	2496.49	0.58	0.40	331	2500.06	0.57	0.41
	Last 70	252	1249.39	0.52	0.50	292	1245.00	0.53	0.61	332	1245.00	0.53	0.61
ip4	First 70	253	994.92	0.64	0.47	293	1250.52	0.44	0.59	333	1247.72	0.44	0.59
	First 30	254	3048.51	0.36	0.41	294	2467.13	0.58	0.35	334	2472.11	0.58	0.35
	Last 30	255	3015.46	0.38	0.47	295	2530.42	0.56	0.38	335	2529.42	0.56	0.38
	Last 70	256	1289.06	0.49	0.51	296	1286.68	0.49	0.62	336	1286.49	0.49	0.62
ip5	First 70	257	1198.35	0.48	0.40	297	1287.20	0.40	0.50	337	1287.20	0.40	0.50
	First 30	258	3017.98	0.38	0.44	298	2503.55	0.57	0.36	338	2503.55	0.57	0.36
	Last 30	259	3104.51	0.35	0.52	299	2572.59	0.55	0.46	339	2571.81	0.55	0.46
	Last 70	260	1269.49	0.51	0.49	300	1311.62	0.48	0.57	340	1308.17	0.48	0.58
ip6	First 70	261	1019.99	0.63	0.45	301	1228.82	0.46	0.53	341	1221.63	0.46	0.52
	First 30	262	3128.91	0.33	0.44	302	2513.76	0.57	0.37	342	2513.76	0.57	0.37
	Last 30	263	3080.48	0.36	0.50	303	2596.75	0.54	0.44	343	2595.60	0.54	0.44
	Last 70	264	1303.95	0.48	0.50	304	1315.70	0.48	0.58	344	1315.70	0.48	0.58
ip7	First 70	265	1257.24	0.43	0.52	305	1197.25	0.48	0.39	345	1257.24	0.43	0.52
	First 30	266	3071.14	0.36	0.45	306	2523.39	0.57	0.37	346	2523.39	0.57	0.37
	Last 30	267	3151.80	0.33	0.55	307	2554.27	0.56	0.45	347	2548.69	0.56	0.45
	Last 70	268	1278.03	0.51	0.46	308	1358.82	0.44	0.58	348	1351.52	0.45	0.58
ip8	First 70	269	1027.72	0.62	0.44	309	1205.72	0.48	0.54	349	1202.40	0.48	0.55
	First 30	270	3170.38	0.31	0.45	310	2535.73	0.56	0.37	350	2534.86	0.56	0.37
	Last 30	271	3145.96	0.33	0.54	311	2640.95	0.53	0.46	351	2638.32	0.53	0.46
	Last 70	272	1307.34	0.48	0.47	312	1343.88	0.45	0.57	352	1344.89	0.45	0.57
ip9	First 70	273	1252.57	0.44	0.39	313	1281.42	0.41	0.49	353	1281.22	0.41	0.49
	First 30	274	3055.09	0.37	0.44	314	2562.64	0.55	0.35	354	2563.04	0.55	0.35
	Last 30	275	3214.01	0.30	0.59	315	2594.82	0.55	0.47	355	2593.54	0.55	0.47
	Last 70	276	1280.90	0.50	0.45	316	1349.12	0.45	0.53	356	1344.03	0.45	0.53
ip10	First 70	277	1101.79	0.57	0.44	317	1228.90	0.46	0.51	357	1223.70	0.47	0.52
	First 30	278	3135.14	0.33	0.43	318	2576.29	0.55	0.35	358	2573.57	0.55	0.36
	Last 30	279	3203.20	0.31	0.58	319	2675.08	0.52	0.48	359	2675.08	0.52	0.48
	Last 70	280	1307.10	0.48	0.45	320	1332.63	0.46	0.53	360	1332.63	0.46	0.53

Table 7
October Results of Mandaleshwar With Trial and Error.

Model Name	Training percentage	Model No.	RBF Kernel			Model No.	LINEAR Kernel			Model No.	POLYNOMIAL Kernel		
			RMSE	CE	MARE		RMSE	CE	MARE		RMSE	CE	MARE
ip1	First 70	361	133.81	0.69	0.22	401	141.41	0.65	0.25	441	141.92	0.65	0.25
	First 30	362	392.67	0.52	0.34	402	382.07	0.55	0.26	442	382.30	0.80	0.26
	Last 30	363	623.82	0.46	0.15	403	605.83	0.49	0.12	443	604.60	0.49	0.12
	Last 70	364	693.17	0.52	0.29	404	708.19	0.50	0.26	444	708.13	0.50	0.26
ip2	First 70	365	200.36	0.30	0.38	405	139.69	0.66	0.24	445	139.62	0.66	0.24
	First 30	366	458.67	0.35	0.46	406	390.33	0.53	0.24	446	390.57	0.53	0.24
	Last 30	367	677.79	0.36	0.26	407	600.60	0.50	0.12	447	600.19	0.50	0.12
	Last 70	368	693.45	0.52	0.29	408	707.40	0.50	0.26	448	707.43	0.50	0.26
ip3	First 70	369	160.53	0.55	0.31	409	123.77	0.73	0.22	449	123.73	0.73	0.22
	First 30	370	494.14	0.23	0.28	410	400.48	0.50	0.23	450	400.44	0.50	0.23
	Last 30	371	670.00	0.38	0.22	411	587.78	0.52	0.13	451	586.51	0.52	0.13
	Last 70	372	712.89	0.50	0.34	412	695.52	0.53	0.25	452	695.47	0.53	0.25
ip4	First 70	373	122.89	0.74	0.21	413	121.67	0.74	0.21	453	121.67	0.74	0.21
	First 30	374	503.86	0.20	0.30	414	406.81	0.48	0.21	454	406.69	0.48	0.21
	Last 30	375	615.05	0.48	0.15	415	590.22	0.52	0.14	455	590.21	0.52	0.14
	Last 70	376	694.43	0.53	0.28	416	695.54	0.53	0.25	456	695.38	0.53	0.25
ip5	First 70	377	147.70	0.62	0.22	417	127.94	0.72	0.22	457	127.94	0.72	0.22
	First 30	378	523.38	0.14	0.32	418	407.98	0.48	0.22	458	407.98	0.48	0.22
	Last 30	379	638.65	0.44	0.16	419	594.49	0.51	0.14	459	594.58	0.51	0.14
	Last 70	380	692.47	0.54	0.26	420	700.99	0.52	0.26	460	780.41	0.41	0.62
ip6	First 70	381	171.02	0.50	0.34	421	121.77	0.74	0.21	461	121.71	0.74	0.21
	First 30	382	561.76	0.01	0.32	422	414.81	0.46	0.20	462	414.71	0.46	0.20
	Last 30	383	679.99	0.36	0.21	423	590.80	0.52	0.14	463	590.77	0.52	0.14
	Last 70	384	697.31	0.53	0.29	424	699.64	0.53	0.27	464	699.64	0.53	0.27
ip7	First 70	385	179.72	0.44	0.28	425	136.77	0.68	0.23	465	136.71	0.68	0.23
	First 30	386	584.54	-0.07	0.33	426	413.02	0.46	0.24	466	413.02	0.46	0.24
	Last 30	387	702.15	0.32	0.18	427	593.53	0.52	0.15	467	604.59	0.50	0.17
	Last 70	388	696.35	0.53	0.28	428	709.87	0.52	0.25	468	708.03	0.52	0.26
ip8	First 70	389	175.16	0.47	0.32	429	131.39	0.70	0.22	469	131.36	0.70	0.22
	First 30	390	565.36	-0.01	0.34	430	424.36	0.43	0.22	470	424.36	0.43	0.22
	Last 30	391	678.09	0.37	0.19	431	589.24	0.52	0.15	471	587.91	0.52	0.15
	Last 70	392	694.69	0.54	0.31	432	710.69	0.51	0.25	472	710.37	0.52	0.25
ip9	First 70	393	173.87	0.48	0.27	433	139.36	0.67	0.22	473	139.40	0.67	0.22
	First 30	394	565.22	-0.04	0.34	434	407.71	0.46	0.25	474	407.71	0.46	0.25
	Last 30	395	652.48	0.41	0.18	435	602.64	0.50	0.15	475	602.71	0.50	0.15
	Last 70	396	693.26	0.55	0.28	436	705.12	0.53	0.26	476	705.13	0.53	0.25
ip10	First 70	397	174.07	0.48	0.27	437	135.25	0.69	0.22	477	135.19	0.69	0.22
	First 30	398	575.88	-0.08	0.35	438	419.30	0.43	0.23	478	419.29	0.43	0.23
	Last 30	399	640.86	0.44	0.17	439	597.56	0.51	0.15	479	597.56	0.72	0.15
	Last 70	400	690.34	0.55	0.28	440	705.07	0.53	0.25	480	704.92	0.53	0.25

For combined four monthly model using the method of trial and error for input selection and calibrated with RBF kernel and last 70 % data RMSE of 1606.53 m^3/s was obtained (model 496). While linear kernel and calibration with last 70 % data of shows RMSE of 1633.71 m^3/s (model 524) and polynomial kernel and calibration with last 70 % data show RMSE of 1609 m^3/s (model 576). Method of AMI for input selection and calibration with RBF kernel and last 70 % data exhibited RMSE as 1555 m^3/s (model 620). For model developed with linear kernel showed RMSE equal to 1679.3 m^3/s (model 640) with last 70 % data used for calibration. The polynomial kernel, when used with last 70 % data for calibration, showed RMSE equal to 1679.1 m^3/s (model 660). Method of correlation analysis for input selection and RBF kernel yielded RMSE of 1606.5 m^3/s (model 680) when last 70 % of data was used. The combination of linear kernel and last 70 % data for calibration showed RMSE of 1691.9 m^3/s (model 700). Polynomial kernel with last 70 % data for calibration exhibited RMSE of 1609 m^3/s (model 720). Thus the results of combined four monthly models indicate that RBF kernel along with trial and error is the best in this case. Results of combined four monthly models are shown in Table 8, 9 and 10.

The models were then judged for their performance at extreme events. For the month of July, the best model with AMI (model 603) and RBF predicted discharge of 19467 m^3/s against an observed discharge of 20119 m^3/s (figure 3) in testing while the maximum value of observed discharge in calibration data set was 36045 m^3/s. For the month of August, the best model with AMI (model 608) and RBF predicted discharge of 8464.8 m^3/s against an observed discharge of 23313 m^3/sin testing (figure 4) wherein the observed maximum value (27093 m^3/s) of discharge was in the calibration data. In case of September as well the maximum observed value of discharge (35450 m^3/s) was included in calibration data set. The best model with AMI and RBF (model 253) yielded 8561.8 m^3/s of discharge in testing against 11852 m^3/s of observed discharge (not shown). For the month of October the best model (model 373) using Trial and error and RBF gave1094.7 m^3/s of discharge against 1628 m^3/s in testing (not shown) when the maximum value of discharge in calibration was 5848 m^3/s. For combined four monthly model maximum value of discharge was 36045 m^3/s which were in the calibration data set. The best model with AMI and RBF (model 620) predicted 5486.4 m^3/s discharge against 23313 m^3/s of observed discharge in testing (figure 5). Thus it can be said results for peak prediction are poor in almost all the cases. This can be attributed to less number of extreme events in the data used. To verify this, the data was analysed for share of extreme events in the entire data length. It was observed that around 1.77 % values of discharge are in the range of 1 m^3/s to 100 m^3/s, 43.16 % values of discharge are in range of 101 m^3/s to 1000 m^3/s, 51.23 % values of discharge in data are in between 1000 m^3/s to 10000 m^3/s, 3.03 % values of discharge are in the range of 10001 m^3/s to 20000 m^3/s, 0.59 % values of discharge are in the range of 20001 m^3/s to 30000 m^3/s, 0.22 % values of discharge are in the range of 30001 m^3/s to 40000 m^3/s. This is similar to other data-driven methods like ANN as mentioned by [31] in their work on wave forecasting.

Table 8
4 Monthly Results of Mandaleshwar With Trial and Error.

Model Name	Training percentage	Model No.	RBF Kernel			Model No.	LINEAR Kernel			Model No.	POLYNOMIAL Kernel		
			RMSE	CE	MARE		RMSE	CE	MARE		RMSE	CE	MARE
ip1	First 70	481	2500.50	0.35	0.63	521	2576.56	0.31	0.75	561	2576.56	0.31	0.75
	First 30	482	2604.59	0.58	0.70	522	2615.26	0.57	0.67	562	2624.05	0.57	0.48
	Last 30	483	2359.51	0.61	0.99	523	2425.05	0.59	1.09	563	2425.05	0.59	1.09
	Last 70	484	1633.36	0.57	0.89	524	1633.71	0.57	1.17	564	1633.71	0.57	1.17
ip2	First 70	485	2444.43	0.38	0.63	525	2575.45	0.31	0.75	565	2460.93	0.37	0.43
	First 30	486	2645.26	0.56	0.61	526	2625.78	0.57	0.66	566	2627.17	0.57	0.66
	Last 30	487	2403.55	0.60	1.00	527	2467.37	0.58	1.12	567	2467.92	0.58	1.12
	Last 70	488	1616.28	0.58	1.24	528	1648.72	0.56	1.16	568	1648.72	0.56	1.16
ip3	First 70	489	2416.07	0.40	0.64	529	2597.42	0.3	0.86	569	2464.3	0.37	0.5
	First 30	490	2578.12	0.58	0.63	530	2595.6	0.58	0.69	570	2466.89	0.62	0.52
	Last 30	491	2294.97	0.64	0.89	531	2464.74	0.58	1.22	571	2464.5	0.58	1.21
	Last 70	492	1632.45	0.57	1.12	532	1662.79	0.56	1.29	572	1669.19	0.55	0.63
ip4	First 70	493	2336.41	0.44	0.56	533	2588.31	0.31	0.87	573	2401.12	0.4	0.46
	First 30	494	2617.14	0.57	0.56	534	2613.26	0.57	0.67	574	2520.43	0.6	0.43
	Last 30	495	2272.93	0.64	0.84	535	2463.13	0.58	1.21	575	2212.16	0.66	0.68
	Last 70	496	1606.53	0.58	0.76	536	1691.93	0.54	0.01	576	1609	0.59	0.003
ip5	First 70	497	3255.46	-0.10	0.69	537	2567.22	0.59	0.65	577	2553.41	0.33	0.46
	First 30	498	2531.40	0.60	0.54	538	2619.17	0.29	0.74	578	2565.84	0.59	0.65
	Last 30	499	2339.21	0.62	0.85	539	2453.78	0.58	1.15	579	2453.98	0.58	1.15
	Last 70	500	1644.14	0.56	0.75	540	1664.37	0.56	0.003	580	1663.85	0.56	0.003
ip6	First 70	501	3106.59	0.00	0.65	541	2616.57	0.29	0.73	581	2614.24	0.29	0.73
	First 30	502	2543.89	0.60	0.47	542	2585.75	0.58	0.64	582	2583.95	0.58	0.64
	Last 30	503	2287.27	0.64	0.79	543	2452.84	0.58	1.15	583	2453.25	0.58	1.15
	Last 70	504	1608.11	0.58	0.72	544	1681.23	0.55	0.003	584	1682.81	0.55	0.003
ip7	First 70	505	2412.74	0.40	0.52	545	2630.32	0.29	0.74	585	2624.18	0.29	0.75
	First 30	506	2550.05	0.59	0.51	546	2560.91	0.59	0.65	586	2561.17	0.59	0.65
	Last 30	507	2393.01	0.60	0.82	547	2496.91	0.57	1.17	587	2497.08	0.57	1.17
	Last 70	508	1642.27	0.57	0.70	548	1660.52	0.56	0	588	1661.21	0.56	0
ip8	First 70	509	2345.51	0.43	0.49	549	2579.76	0.58	0.62	589	2623.17	0.29	0.74
	First 30	510	3273.05	0.33	0.61	550	2623.05	0.29	0.75	590	2579.76	0.58	0.62
	Last 30	511	2387.17	0.61	0.79	551	2495.87	0.57	1.17	591	2495.87	0.57	1.17
	Last 70	512	1608.10	0.74	0.67	552	1678.41	0.55	0.002	592	1675.01	0.55	0.002
ip9	First 70	513	2413.74	0.40	0.48	553	2634.1	0.29	0.7	593	2558.12	0.59	0.62
	First 30	514	2647.70	0.56	0.53	554	2558.12	0.59	0.62	594	1667.73	0.55	0.99
	Last 30	515	2423.64	0.59	0.80	555	2471.12	0.58	1.08	595	2627.42	0.29	0.71
	Last 70	516	1644.37	0.56	0.67	556	1670.2	0.55	0.003	596	2472.23	0.58	0.004
ip10	First 70	517	2359.43	0.43	0.46	557	2626.88	0.29	0.71	597	2626.58	0.29	0.7
	First 30	518	2674.81	0.55	0.47	558	2576.75	0.59	0.6	598	2576.75	0.59	0.6
	Last 30	519	2395.82	0.60	0.76	559	2467.8	0.58	1.08	599	2470.54	0.58	1.08
	Last 70	520	1611.71	0.58	0.64	560	1686.08	0.54	0.004	600	1684.42	0.54	0.004

Table 9
Mandaleshwar Results and Input details with AMI.

Training Percentage	Model No.	RBF Kernel			Model No.	LINEAR Kernel			Model No.	POLYNOMIAL Kernel		
		RMSE	CE	MARE		RMSE	CE	MARE		RMSE	CE	MARE
	July						$^{R}t,{}^{Q}t-1,{}^{Q}t$					
First 70	601	3665.6	0.69	1.06	621	3717.9	0.61	0.93	641	3717.9	0.61	0.93
First 30	602	3926.7	0.52	1.86	622	3222.1	0.58	1.71	642	3222.1	0.58	1.71
Last 30	603	55.9	0.99	2.22	623	2786.4	0.26	1.65	643	2755.1	0.27	1.58
Last 70	604	1929	0.24	1.36	624	2064.7	-0.65	1.41	644	2064.7	-0.65	1.41
	August					$^{R}t-2,{}^{R}t-1,{}^{R}t,{}^{Q}t$						
First 70	605	2721.3	0.71	0.59	625	2705.2	0.46	0.56	645	2705.3	0.46	0.56
First 30	606	2840.9	0.78	0.4	626	2840.9	0.55	0.4	646	2840.9	0.55	0.4
Last 30	607	2864.2	0.78	1.17	627	2628.6	0.62	0.94	647	2622.1	0.62	0.93
Last 70	608	2426.3	0.77	2.11	628	2454.1	0.56	1.93	648	2453.6	0.56	1.95
	September					$^{R}t-2,{}^{R}t-1,{}^{R}t,{}^{Q}t$						
First 70	609	1503.9	0.18	0.59	629	1706.1	-0.06	0.59	649	1700.7	-0.05	0.59
First 30	610	2797	0.46	0.37	630	2294.5	0.64	0.3	650	2290.7	0.64	0.3
Last 30	611	2874.4	0.44	0.44	631	2397.5	0.61	0.35	651	2397.2	0.61	0.35
Last 70	612	1215.8	0.55	0.57	632	1323.5	0.46	0.49	652	1323.6	0.46	0.49
	October					$^{R}t-4,{}^{R}t-3,{}^{R}t-1,{}^{R}t,{}^{Q}t-2,{}^{Q}t-1,{}^{Q}t$						
First 70	613	194	0.35	0.34	633	125.9	0.73	0.21	653	125.8	0.73	0.21
First 30	614	556.5	0.04	0.36	634	417.3	0.46	0.19	654	417.3	0.46	0.19
Last 30	615	673.3	0.38	0.17	635	598.5	0.51	0.13	655	598.6	0.51	0.13
Last 70	616	708.9	0.51	0.3	636	700.7	0.52	0.26	656	700.3	0.53	0.26
	4 Monthly					$^{R}t-3,{}^{R}t-2,{}^{R}t-1,{}^{R}t,{}^{Q}t-1,{}^{Q}t$						
First 70	617	1637	0.72	0.48	637	1917.6	0.62	0.68	657	1916.5	0.62	0.68
First 30	618	2155.7	0.71	0.4	638	2233.1	0.69	0.47	658	2232.8	0.69	0.47
Last 30	619	2082.2	0.7	0.63	639	2194.7	0.67	0.75	659	2195	0.67	0.75
Last 70	620	1555	0.61	0.74	640	1679.3	0.55	1	660	1679.1	0.55	1.06

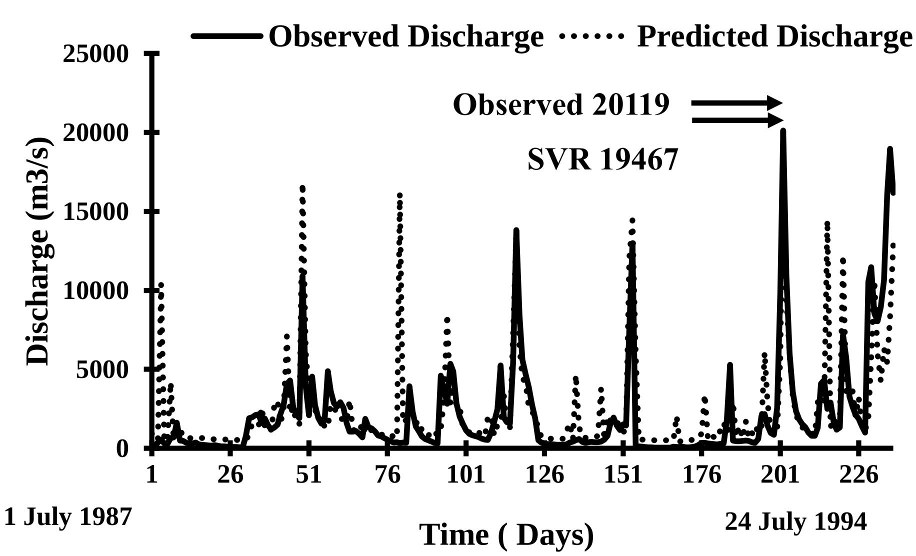


Fig. 3. Mandaleshwar July last 30% calibration with AMI method of input selection.

Table 10
Mandaleshwar Results and Inputs with Method of Correlation Analysis.

Training Percenatge	Model No.	RBF Kernel			Model No.	LINEAR Kernel			Model No.	POLYNOMIAL Kernel		
		RMSE	CE	MARE		RMSE	CE	MARE		RMSE	CE	MARE
	July $^{R}t,^{Q}t\text{-}1,^{Q}t$											
First 70	661	4541.9	0.4	1.5	681	4812.2	0.33	1.5	701	4834	0.32	1.46
First 30	662	4471.2	0.18	1.98	682	3766.3	0.42	2.03	702	3766.3	0.42	2.03
Last 30	663	2261.1	0.54	3.88	683	2173.1	0.58	3.63	703	2178.1	0.58	3.65
Last 70	664	1414.7	0.22	2.02	684	1460.6	0.18	2.18	704	1459.8	0.18	2.19
August $^{R}t\text{-}2,^{R}t\text{-}1,^{R}t,^{Q}t$												
First 70	665	2843	0.4	0.58	685	2971.2	0.35	0.6	705	2966.2	0.35	0.6
First 30	666	2945	0.52	0.45	686	2974.3	0.51	0.44	706	2974.8	0.76	0.44
Last 30	667	3049	0.48	1.17	687	2935	0.52	1.06	707	2941.1	0.52	1.07
Last 70	668	2576.6	0.51	1.93	688	2574.4	0.51	2.15	708	2574.1	0.51	2.16
September $^{R}t\text{-}2,^{R}t\text{-}1,^{R}t,^{Q}t$												
First 70	669	1066.7	0.84	0.46	689	1171	0.51	0.45	709	1162.3	0.51	0.46
First 30	670	3102.7	0.6	0.42	690	2491.4	0.57	0.35	710	2496.5	0.57	0.35
Last 30	671	3041.4	0.62	0.5	691	2640	0.53	0.42	711	2639.1	0.53	0.42
Last 70	672	1277.1	0.79	0.51	692	1229.5	0.54	0.55	712	1229.5	0.54	0.55
October $^{R}t\text{-}4,^{R}t\text{-}3,^{R}t\text{-}1,^{R}t,^{Q}t\text{-}2,^{Q}t\text{-}1,^{Q}t$												
First 70	673	134.1	0.94	0.22	693	123.9	0.74	0.22	713	123.9	0.74	0.22
First 30	674	507.5	0.62	0.33	694	406.1	0.46	0.22	714	406.1	0.46	0.22
Last 30	675	607.1	0.71	0.15	695	598	0.51	0.13	715	598.1	0.51	0.13
Last 70	676	701.2	0.71	0.27	696	702.4	0.53	0.26	716	702.2	0.53	0.27
4 Monthly $^{R}t\text{-}3,^{R}t\text{-}2,^{R}t\text{-}1,^{R}t,^{Q}t\text{-}1,^{Q}t$												
First 70	677	2336.4	0.44	0.56	697	2588.3	0.31	0.87	717	2401.1	0.4	0.46
First 30	678	2617.1	0.57	0.56	698	2613.3	0.57	0.67	718	2520.4	0.6	0.43
Last 30	679	2272.9	0.64	0.84	699	2463.1	0.58	1.21	719	2212.2	0.66	0.68
Last 70	680	1606.5	0.58	0.76	700	1691.9	0.54	0.01	720	1609	0.59	0.0031

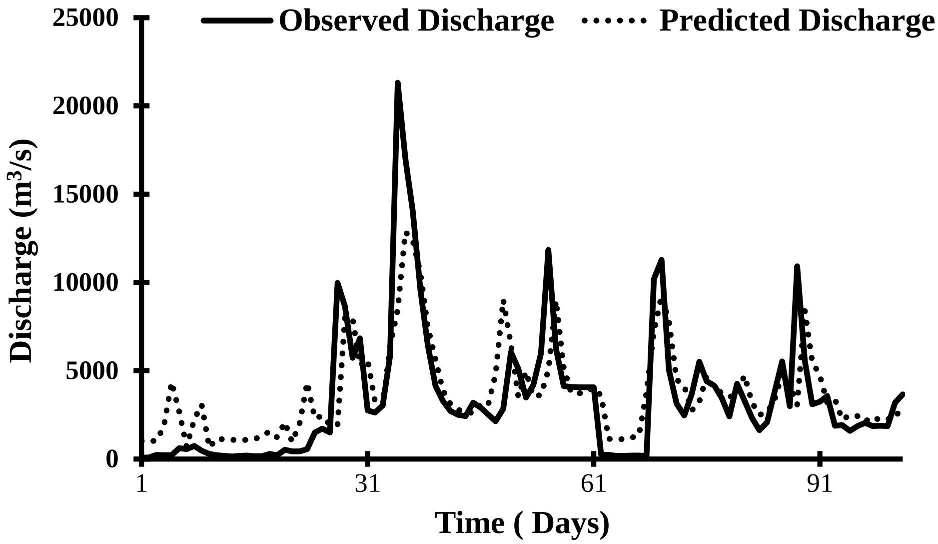


Fig. 4. Mandaleshwar August first 30% calibration with AMI method of input selection.

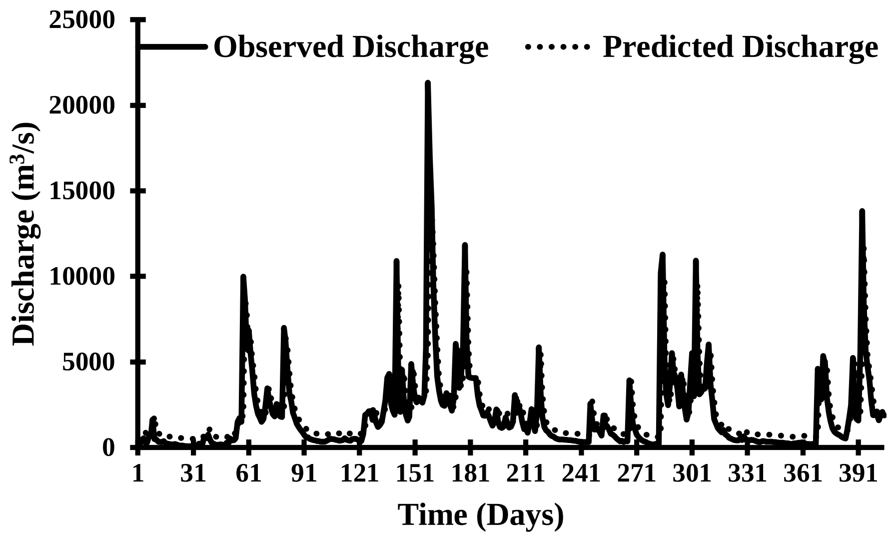


Fig. 5. Mandaleshwar 4 Monthly first 70% calibration with AMI method of input selection.

After screening the Mandaleshwar results particularly for the input selection method of trial and error, it was observed that increase in lags of rainfall and discharge beyond ip5 (that is 3 previous values of discharge and 2 previous values of rainfall) did not influence the accuracy of the models significantly. This was true for all monthly and four monthly models as well. This also proved the less influence of previous values of rainfall on stream flow. It may be noted that the rainfall is measured at the same location as the discharge measurement station in all the above locations and thus its influence on discharge is not expected to go for many previous time steps. Thus it seems that the data-driven technique of SVR has understood the philosophy of rainfall-runoff process definitely up to a certain extent. Secondly, it was also observed that the RMSE values were in thousands in some cases. However, it can be seen that the maximum value of discharge at Mandaleshwar is 36045 m^3/s in July. Therefore the RMSE can be of higher magnitudes. Overally, it can be seen that October results were better as compared to all other months with all three input selection methods. This can be attributed to the lowest average rainfall and lowest standard deviation for October. Refer table number 4 to 10 for results at Mandaleshwar. Results in bold letters indicate the best model.

Among the three kernels used, RBF kernel seemed to be the best as evident from the results. The reason for RBF to be the best in comparison with other kernel functions could lie in the fact that the RBF kernel is more compact and is able to shorten the computational training process and improve the generalization performance of LS-SVR [21]. Performance of the linear and polynomial kernels is almost the same. Controlling parameter of the polynomial kernel is a degree (d), which was varied and models with best results were finalized. In many cases, it was found that 'd' had a value equal to '1' which ultimately resulted into a ‘Linear Kernel Function’.

At Mandaleshwar all three input selection methods were tried. By observing results at Mandaleshwar AMI and Method of the trial were found to be the best input selection methods. Therefore for remaining two stations namely Nighoje and Budhwad trial and error and AMI methods were used for input selection, and RBF kernel was used for calibration of the model. Results of Nighoje are discussed in the next paragraph.

5.2. Nighoje

Results at Nighoje are shown in Table 11, 12 and 13. For the month of June, model developed with trial and error input selection and last 70 % data for calibration showed RMSE equal to 34.27 m^3/s (model 724), while model developed using input selection method of AMI and calibrated with last 70 % data showed RMSE of 52.29 m^3/s (model 964), which is high as compared to trial and error. The models developed for July calibrated with last 30 % data (model 779), September with last 70 % data (model 879) and five monthly model calibrated with last 30 % data (model 951) followed the same suite while October model, when calibrated with last 70% data, showed equal performance of both the input selection schemes (model 844 and model 980). For the month of August, a model with input selection method of trial and error and calibrated with first 30 % data yielded RMSE of 89.05 m^3/s (model 814), while model calibrated with input selection method of AMI and first 30% data gave RMSE of 85.15 m^3/s (model 970). Thus for Nighoje majority of the times, the models developed with input selection method of trial and error were the winners possibly due to its nonlinear nature.

June model had a maximum value of discharge as 678.16 m^3/s which were included in the calibration data set. The best model (model 724) predicted discharge as 94.46 m^3/s against 198 m^3/s in testing (not shown). For July the best model (model 779) predicted 263.49 m^3/s against an observed discharge of 576.92 m^3/s in testing (not shown). The maximum value of discharge in calibration was 1299.62 m^3/s. For August model maximum value of discharge was 2110.92 m^3/s which were in the calibration data set. The best model (model 970) predicted 481.18 m^3/s against 893.05 m^3/s observed discharge in testing. Scatter plot for the month of August is shown in figure 6. For September model maximum value of discharge in calibration data was 446.09 m^3/s. The best model (model 879) yielded 98.06 m^3/s discharge against an observed discharge of 260.18 m^3/s (not shown). In five Monthly combined model (model 951) the maximum observed discharge was 2110.92 m^3/s which were predicted as 516.22 m^3/s in testing. The maximum value of discharge in calibration was 1299.62 m^3/s. Figure 7 shows scatter plot for 5 Monthly model. For Nighoje results of the models developed for the month October results are better as far as general performance is considered as compared to all other months which are similar to Mandaleshwar wherein results of October are the best. The peaks were predicted with less accuracy as in Mandaleshwar. Statistical analysis of data showed that, 82 % values of discharge were in the range of 1 m^3/s to 100 m^3/s, 17 % values of discharge were in the range of 101 m^3/s to 1000 m^3/s, 0.24 % values of discharge were in the range of 1001 m^3/s to 2000 m^3/s with 0.76% above 2000 m^3/s.

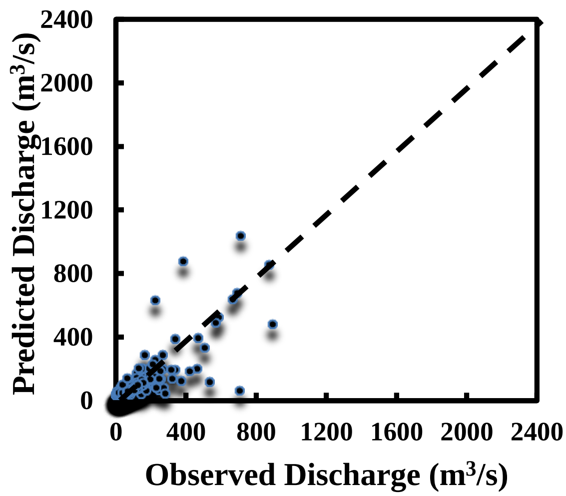


Fig. 6. Nighoje August first 30% calibration with AMI method of input selection.

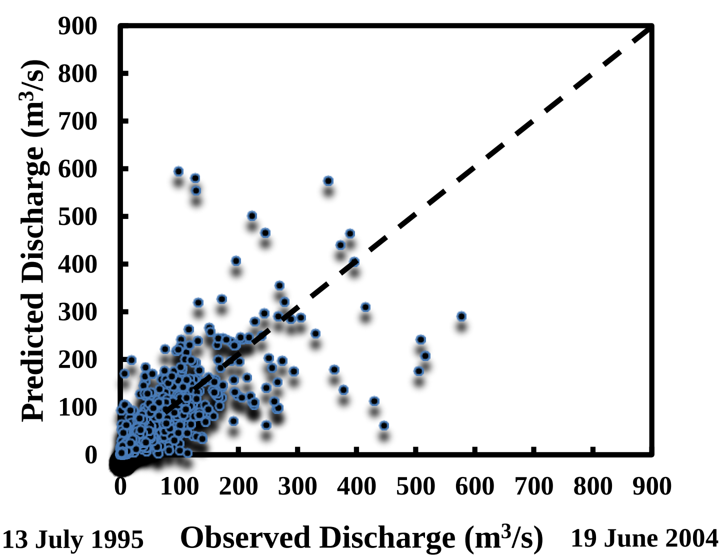


Fig. 7. Nighoje 5 Monthly ip8 last 30% calibration with Trial and Error method of input selection.

Table 11
Nighoje Results With Trial and Error.

Model Name	Training percentage	Model No.	June			Model No.	July			Model No.	August		
			RMSE	CE	MARE		RMSE	CE	MARE		RMSE	CE	MARE
ip1	First 70	721	100.92	0.30	1.72	761	140.19	0.44	1.35	801	127.94	0.46	0.35
	First 30	722	79.52	0.27	1.87	762	96.14	0.52	1.70	802	121.16	0.23	2.74
	Last 30	723	53.86	0.01	14.26	763	70.04	0.46	7.92	803	182.28	-0.31	6.84
	Last 70	724	34.27	0.26	13.33	764	87.33	0.48	7.65	804	212.74	0.11	2.02
ip2	First 70	725	99.55	0.32	1.67	765	140.51	0.44	1.15	805	165.33	0.1	0.48
	First 30	726	80.49	0.26	1.88	766	92.51	0.55	1.41	806	125.58	0.17	2.96
	Last 30	727	57.97	-0.14	12.22	767	76.60	0.36	7.83	807	170.31	-0.15	6.27
	Last 70	728	44.71	-0.25	14.40	768	89.97	0.44	9.90	808	201.61	0.2	1.88
ip3	First 70	729	104.12	-8.63	0.90	769	148.72	0.37	1.14	809	120.46	0.52	0.36
	First 30	730	82.56	0.22	1.92	770	100.41	0.47	1.48	810	93.84	0.54	1.61
	Last 30	731	52.83	0.04	12.84	771	70.21	0.46	7.27	811	136.83	0.27	2.77
	Last 70	732	35.43	0.43	12.28	772	89.12	0.45	6.15	812	203.41	0.19	0.82
ip4	First 70	733	103.05	0.27	1.55	773	148.94	0.37	0.97	813	114.65	0.57	0.31
	First 30	734	83.21	0.21	1.91	774	98.25	0.49	1.28	814	89.05	0.58	0.9916
	Last 30	735	56.76	-0.11	11.34	775	75.13	0.38	7.17	815	112.11	0.51	2.79
	Last 70	736	43.36	-0.16	12.99	776	99.50	0.32	8.55	816	180.69	0.36	1.22
ip5	First 70	737	105.14	0.24	1.66	777	150.46	0.36	1.11	817	93.14	0.6	0.63
	First 30	738	83.86	0.20	2.05	778	100.89	0.47	1.45	818	93.68	0.54	1.61
	Last 30	739	52.84	0.06	12.65	779	69.68	0.47	6.38	819	137.56	0.26	2.74
	Last 70	740	35.55	0.22	12.10	780	89.73	0.64	5.46	820	204.14	0.19	0.7
ip6	First 70	741	103.39	0.26	1.57	781	150.92	0.35	0.94	821	115.59	0.56	0.33
	First 30	742	84.36	0.19	2.02	782	98.93	0.49	1.22	822	92.9	0.55	0.96
	Last 30	743	55.52	-0.03	11.02	783	74.49	0.39	6.67	823	112.79	0.51	2.7
	Last 70	744	41.78	-0.08	13.10	784	101.04	0.30	7.62	824	181.94	0.35	0.0114
ip7	First 70	745	107.19	0.21	1.59	785	149.76	0.36	1.14	825	122.09	0.51	0.36
	First 30	746	86.69	0.13	3.24	786	100.66	0.47	1.36	826	93.88	0.54	1.6
	Last 30	747	56.13	-0.05	15.31	787	69.78	0.47	6.22	827	138.16	0.26	2.82
	Last 70	748	44.78	0.38	13.57	788	90.32	0.44	5.59	828	204.45	0.19	0.011
ip8	First 70	749	105.34	0.23	1.49	789	148.92	0.37	0.98	829	115.16	0.56	0.33
	First 30	750	84.98	0.16	3.00	790	97.66	0.50	1.13	830	95.51	0.52	0.9
	Last 30	751	57.25	-0.09	13.12	791	75.07	0.39	6.56	831	113.63	0.5	2.7
	Last 70	752	43.87	0.19	13.76	792	102.48	0.28	7.42	832	193.02	0.38	0.0116
ip9	First 70	753	109.23	0.19	1.37	793	148.75	0.37	1.16	833	123.12	0.5	0.36
	First 30	754	88.18	0.10	3.63	794	101.13	0.47	1.38	834	103.47	0.44	1.97
	Last 30	755	59.18	-0.16	15.26	795	70.20	0.47	6.36	835	138.73	0.26	2.79
	Last 70	756	44.59	0.18	10.21	796	90.15	0.64	5.84	836	205.83	0.18	0.0129
ip10	First 70	757	107.37	0.22	1.37	797	148.02	0.38	1.01	837	115.13	0.56	0.33
	First 30	758	86.43	0.13	3.36	798	98.70	0.49	1.17	838	96.61	0.51	0.87
	Last 30	759	58.52	-0.14	12.69	799	75.86	0.38	6.57	839	114.29	0.5	2.65
	Last 70	760	44.06	0.20	10.89	800	103.15	0.52	20.81	840	180.3	0.37	0.0135

Table 12
Nighoje Results With Trial and Error.

Model Name	Training percentage	Model No.	September			Model No.	October			Model No.	5 Monthly		
			RMSE	CE	MARE		RMSE	CE	MARE		RMSE	CE	MARE
ip1	First 70	841	35.64	0.55	0.41	881	10.82	0.999	0.68	921	90.82	0.62	0.76
	First 30	842	38	-27.9	0.66	882	10.53	0.450	0.82	922	22.75	0.69	0.83
	Last 30	843	33.79	0.31	1.94	883	22.42	0.999	2.35	923	3.25	0.08	10.57
	Last 70	844	45.04	0.27	0.01	884	1.17	0.998	0.12	924	106.89	0.37	1.06
ip2	First 70	845	54.17	-0.05	0.77	885	10.02	0.999	0.48	925	113.76	0.41	2.21
	First 30	846	41.95	0.07	2.73	886	9.87	0.772	1.07	926	64.09	0.65	1.79
	Last 30	847	33.14	0.34	1.87	887	22.12	0.999	2.31	927	1.47	0.48	2.16
	Last 70	848	44.06	0.3	0.01	888	28.85	0.242	0.09	928	103	0.41	4.15
ip3	First 70	849	35.47	0.55	0.37	889	10.71	0.999	0.98	929	91.02	0.62	0.72
	First 30	850	26.38	0.63	1.03	890	10.53	0.451	1.13	930	62.18	0.67	1.42
	Last 30	851	45.76	0.25	0.52	891	20.8	0.999	1.27	931	1.79	0.39	3.19
	Last 70	852	45.14	0.27	0	892	28.56	0.256	0.09	932	108.7	0.35	0.99
ip4	First 70	853	33.59	0.6	0.38	893	10.82	0.999	1.05	933	63.52	0.66	1.57
	First 30	854	25.38	0.66	1.008	894	10.53	0.45	1	934	87.73	0.65	0.85
	Last 30	855	32.73	0.36	1.5168	895	22.42	0.999	2.1	935	1.09	0.49	1.2
	Last 70	856	45.08	0.27	0.0011	896	1.17	0.998	0.12	936	103.56	0.41	1.14
ip5	First 70	857	36.13	0.53	0.36	897	10.77	0.999	1	937	62.08	0.68	1.34
	First 30	858	29.64	0.54	0.78	898	10.26	0.469	1.23	938	91.66	0.62	0.73
	Last 30	859	22.03	0.53	1.37	899	21.16	0.999	1.25	939	1.67	0.38	2.78
	Last 70	860	26.35	0.48	0.0039	900	29.06	0.236	0.0627	940	109.69	0.34	1.04
ip6	First 70	861	36.07	0.54	0.38	901	10.05	0.999	0.9	941	62.85	0.67	1.44
	First 30	862	29.05	0.55	0.77	902	12.6	0.210	0.89	942	86.77	0.66	0.81
	Last 30	863	21.56	0.55	1.32	903	21.3	0.999	1.54	943	1.06	0.5	1.12
	Last 70	864	24.7	0.54	0.0065	904	29.07	0.236	0.08	944	103.32	0.41	1.08
ip7	First 70	865	36.1	0.53	0.3589	905	10.78	0.999	0.99	945	62.26	0.67	1.34
	First 30	866	27.88	0.59	0.656	906	11.02	0.387	1.51	946	88.43	0.64	0.92
	Last 30	867	21.24	0.54	1.2466	907	21.31	0.999	1.27	947	1.66	0.38	2.74
	Last 70	868	23.77	0.55	0.004	908	29.14	0.240	0.061	948	110.82	0.33	0.98
ip8	First 70	869	35.31	0.56	0.3647	909	10.08	0.999	0.89	949	86.18	0.66	0.82
	First 30	870	27.52	0.6	0.6562	910	9.86	0.512	1.12	950	62.72	0.67	1.32
	Last 30	871	21.13	0.73	1.2079	911	21.4	0.999	1.52	951	0.98	0.49	0.96
	Last 70	872	24.52	0.52	0.0035	912	29.28	0.233	0.0637	952	103.85	0.41	1.04
ip9	First 70	873	36.89	0.52	0.3592	913	10.69	0.999	1.0024	953	89.37	0.64	0.94
	First 30	874	28.85	0.56	0.8137	914	10.52	0.443	1.28	954	63.22	0.66	1.36
	Last 30	875	20.87	0.54	1.1735	915	21.22	0.999	1.3	955	1.31	0.38	1.72
	Last 70	876	22.86	0.55	0.0065	916	28.81	0.259	0.0736	956	111.71	0.31	1.25
ip10	First 70	877	35.59	0.55	0.36	917	9.96	0.999	0.9	957	63.06	0.66	1.26
	First 30	878	26.75	0.62	0.586	918	9.94	0.503	1.14	958	86.75	0.66	0.84
	Last 30	879	20.71	0.55	1.1439	919	21.21	0.999	1.37	959	1.08	0.48	1.16
	Last 70	880	22.64	0.56	0.0063	920	29.25	0.236	0.0826	960	103.92	0.4	1.15

Table 13
Nighoje Results with AMI.

Model No.	Training Percentage	Month/Input	RMSE	CE	MARE
961	First 70	June Rt-1, Rt, Qt	94.25	0.37	1.54
962	First 30		77.87	0.29	2.03
963	Last 30		53.99	-0.01	11.27
964	Last 70		52.29	-0.69	1.18
965	First 70	July Rt-1, Rt, Qt-1, Qt	148.94	0.37	0.97
966	First 30		98.25	0.49	1.28
967	Last 30		75.13	0.38	7.17
968	Last 70		99.5	0.32	8.55
969	First 70	August Rt-1, Rt, Qt	112.84	0.58	0.31
970	First 30		85.15	0.62	1.15
971	Last 30		110.57	0.51	2.36
972	Last 70		164.88	0.47	0.01
973	First 70	September Rt-4,Rt-3, Rt-2,Rt-1, Rt,Qt-1,Qt	31.3	0.65	0.36
974	First 30		31.55	0.48	1.42
975	Last 30		29.4	0.49	1.35
976	Last 70		40.72	0.41	0.001
977	First 70	October Rt-1, Rt, Qt-1,Qt	10.82	0.99996	0.68
978	First 30		10.53	0.45	0.82
979	Last 30		22.42	0.99999	2.35
980	Last 70		1.17	0.99875	0.12
981	First 70	5 Monthly Rt-2, Rt-1 ,Rt, Qt-1, Qt	69.11	0.78	0.46
982	First 30		51.09	0.78	1.06
983	Last 30		68.79	0.5	3.1
984	Last 70		79.76	0.65	0.8

5.3. Budhwad

Consolidated results of Budhwad are shown in Table 14, 15 and 16. For the month of June model with input selection method of trial and error and calibrated with last 30 % data exhibited RMSE of 12.52 m^3/s (model 995), while calibration with last 30 % data and input selection by AMI showed RMSE as 9.36 m^3/s (model 1227). For the month of July model calibrated with last 30 % data along with method of trial and error for input selection showed RMSE of 17.4 m^3/s (model 1039) while AMI and calibration with last 30 % data RMSE showed RMSE of 17.76 m^3/s (model 1231), which are almost similar. For models developed for the month of August with method of trial and error for input selection and calibration with last 30 % data showed RMSE of 17.44 m^3/s (model 1067), while AMI and calibration with last 30 % data showed RMSE of 14.45 m^3/s (model 1235). September month model results showedAMI as clear winner since RMSE with trial and error method of input selection and calibration with last 30 % data was 7.8 m^3/s (model 1119) and calibration with AMI and last 30 % data RMSE was 0.87 m^3/s (model 1240). For the month of October model with input selection method of trial and error and calibration with first 70 % data gave RMSE of 0.92 m^3/s (model 1145), while AMI and calibration with last 70 % data gave RMSE of 0.87 m^3/s (model 1240). For 5 monthly combined model results showed that AMI is the winner. However, there was the very small difference between the results of models developed with trial and error and AMI methods. Trial and error exhibited RMSE of 12.77 m^3/s (model 1195) and AMI 12.19 m^3/s (model 1247). It can be seen that for the majority of the times AMI was the winner at Budhwad.

Table 14
Budhwad Results with Trial and Error.

Model Name	Training percentage	Model No.	June			Model No.	July			Model No.	August		
			RMSE	CE	MARE		RMSE	CE	MARE		RMSE	CE	MARE
ip1	First 70	985	19.95	0.17	1.99	1025	25.21	0.64	0.99	1065	27.62	0.5	0.89
	First 30	986	13.66	0.28	2.57	1026	18.03	0.68	1.87	1066	19.41	0.55	1.57
	Last 30	987	13.45	-0.16	5.66	1027	17.99	0.63	1.76	1067	17.44	0.54	1.71
	Last 70	988	14.66	0.3	0.18	1028	25.25	0.58	0.04	1068	23.87	0.51	0.02
ip2	First 70	989	23.37	-0.14	1.37	1029	24.69	0.65	0.91	1069	33.43	0.26	1.85
	First 30	990	15.9	0.03	3.7	1030	19.37	0.63	2.98	1070	27.17	0.13	4.33
	Last 30	991	15.85	-0.61	7.1	1031	17.69	0.65	1.88	1071	25.52	0.03	4.33
	Last 70	992	17.08	0.05	0.22	1032	23.97	0.62	0.04	1072	30.1	0.22	0.05
ip3	First 70	993	23.62	-0.17	1.36	1033	23.03	0.7	0.6	1073	27.22	0.51	0.83
	First 30	994	16.13	0.01	3.8	1034	17.41	0.7	1.74	1074	19.87	0.53	1.54
	Last 30	995	12.52	0.00	4.38	1035	17.72	0.65	1.89	1075	18.19	0.51	2.1
	Last 70	996	15.95	0.17	0.3	1036	24.54	0.61	0.05	1076	24.53	0.48	0.03
ip4	First 70	997	23.34	-0.14	1.37	1037	24.55	0.66	0.83	1077	24.51	0.6	1.02
	First 30	998	15.37	0.1	3.52	1038	19.41	0.63	2.71	1078	19.49	0.55	2.51
	Last 30	999	12.65	-0.02	4.35	1039	17.4	0.66	1.75	1079	20.15	0.39	2.52
	Last 70	1000	16.41	0.12	0.33	1040	23.93	0.63	0.05	1080	26.55	0.39	0.03
ip5	First 70	1001	23.67	-0.17	1.33	1041	22.87	0.7	0.63	1081	27.94	0.49	0.81
	First 30	1002	15.73	0.07	3.68	1042	17.55	0.7	1.8	1082	19.65	0.54	1.28
	Last 30	1003	13.54	-0.15	5.41	1043	18.03	0.64	1.93	1083	18.2	0.51	2.07
	Last 70	1004	16.09	0.17	0.26	1044	24.79	0.6	0.06	1084	24.68	0.48	0.04
ip6	First 70	1005	21.72	0.01	1.38	1045	24.56	0.66	0.83	1085	24.56	0.6	0.99
	First 30	1006	16.13	0.02	3.79	1046	18.98	0.65	1.92	1086	18.85	0.58	2.2
	Last 30	1007	12.81	-0.03	4.53	1047	17.84	0.64	1.96	1087	18.38	0.5	1.26
	Last 70	1008	16.19	0.15	0.28	1048	24.03	0.63	0.06	1088	26.37	0.41	0.03
ip7	First 70	1009	21.18	0.09	1.33	1049	24.01	0.68	0.7	1089	28.25	0.47	0.82
	First 30	1010	15.4	0.12	3.69	1050	18.29	0.67	2.17	1090	20.41	0.51	1.25
	Last 30	1011	14.63	-0.33	6.35	1051	18.13	0.63	1.86	1091	18.31	0.5	2.03
	Last 70	1012	17.64	0.06	0.65	1052	25.27	0.59	0.06	1092	24.98	0.47	0.05
ip8	First 70	1013	22.02	0	1.25	1053	24.99	0.65	0.86	1093	25.32	0.58	0.9
	First 30	1014	16.17	0.02	3.83	1054	17.78	0.69	2.03	1094	19.07	0.57	2.13
	Last 30	1015	13.96	-0.22	5.79	1055	17.93	0.64	1.89	1095	18.63	0.48	1.54
	Last 70	1016	17.11	0.09	0.65	1056	24.46	0.61	0.06	1096	26.45	0.4	0.04
ip9	First 70	1017	24.02	-0.19	1.25	1057	24.28	0.67	0.77	1097	28.45	0.47	0.85
	First 30	1018	15.67	0.11	3.76	1058	19.19	0.64	2.37	1098	20.9	0.49	1.23
	Last 30	1019	14.46	-0.28	6.17	1059	18.08	0.64	1.79	1099	18.33	0.5	2.02
	Last 70	1020	17.13	0.09	1.02	1060	24.53	0.62	0.07	1100	25.11	0.46	0.07
ip10	First 70	1021	23.74	-0.16	1.27	1061	25	0.65	0.87	1101	25.27	0.58	0.99
	First 30	1022	14.8	0.18	3.49	1062	18.76	0.66	2.15	1102	19.19	0.57	2.09
	Last 30	1023	14.22	-0.25	6.02	1063	17.94	0.64	1.84	1103	18.67	0.48	1.55
	Last 70	1024	16.76	0.11	1.03	1064	23.71	0.64	0.06	1104	27.04	0.37	0.07

Table 15
Budhwad Results with Trial and Error.

Model Name	Training percentage	Model No.	September			Model No.	October			Model No.	5 Monthly		
			RMSE	CE	MARE		RMSE	CE	MARE		RMSE	CE	MARE
ip1	First 70	1105	13.54	0.52	0.56	1145	0.92	0.78	0.32	1185	18.61	0.64	0.76
	First 30	1106	9.85	0.54	0.67	1146	2.04	0.49	0.39	1186	13.83	0.65	1.28
	Last 30	1107	8.28	0.57	0.78	1147	2.09	0.64	0.7	1187	12.77	0.68	1.79
	Last 70	1108	10.34	0.59	0.01	1148	3.56	-	2.72	1188	16.89	0.68	0.09
ip2	First 70	1109	13.76	0.5	0.75	1149	1.05	0.72	0.36	1189	21.2	0.54	2.12
	First 30	1110	10.29	0.5	0.49	1150	2.09	0.46	0.41	1190	18.21	0.39	6.03
	Last 30	1111	8.04	0.6	0.62	1151	3.4	0.05	2.84	1191	14.38	0.6	1.15
	Last 70	1112	10.33	0.59	0.0038	1152	3.56	-	2.72	1192	18.61	0.62	0.08
ip3	First 70	1113	13.88	0.5	0.76	1153	1.02	0.74	0.37	1193	18.01	0.67	0.7
	First 30	1114	9.84	0.54	0.8	1154	2.14	0.43	0.44	1194	13.51	0.66	1.16
	Last 30	1115	8.14	0.50	1.01	1155	2.2	0.6	0.7	1195	12.77	0.68	1.51
	Last 70	1116	9.18	0.58	0.01	1156	1.93	0.7	0.57	1196	16.57	0.7	0.1
ip4	First 70	1117	13.84	0.5	0.86	1157	1.12	0.68	0.4	1197	18.52	0.65	0.89
	First 30	1118	10.35	0.51	0.59	1158	2.22	0.39	0.47	1198	14.04	0.64	2.11
	Last 30	1119	7.86	0.53	0.62	1159	2.24	0.59	0.74	1199	14.75	0.59	1.05
	Last 70	1120	8.6	0.63	0.01	1160	2.1	0.64	0.61	1200	18.55	0.62	0.1
ip5	First 70	1121	13.94	0.49	0.88	1161	1.01	0.74	0.37	1201	18.2	0.66	0.73
	First 30	1122	9.64	0.57	0.75	1162	1.9	0.53	0.37	1202	13.54	0.66	1.11
	Last 30	1123	8.28	0.47	0.97	1163	2.26	0.59	0.7	1203	12.92	0.68	2.01
	Last 70	1124	9.39	0.54	0.01	1164	2.24	0.64	0.79	1204	17.02	0.68	0.13
ip6	First 70	1125	14.11	0.48	0.94	1165	1.1	0.69	0.39	1205	18.41	0.65	0.82
	First 30	1126	10.25	0.51	0.99	1166	2.15	0.4	0.44	1206	13.94	0.64	1.68
	Last 30	1127	8.28	0.47	0.69	1167	2.28	0.58	0.73	1207	14.76	0.59	1.07
	Last 70	1128	8.94	0.59	0.01	1168	2.3	0.62	0.46	1208	18.56	0.62	0.13
ip7	First 70	1129	13.96	0.49	0.86	1169	1.48	0.45	0.47	1209	18.29	0.66	0.87
	First 30	1130	9.76	0.56	0.78	1170	2.39	0.26	0.64	1210	13.73	0.65	1.17
	Last 30	1131	8.47	0.43	0.93	1171	2.19	0.61	0.63	1211	13.03	0.67	2.03
	Last 70	1132	9.99	0.46	0.01	1172	2.32	0.7	0.91	1212	17.31	0.67	0.31
ip8	First 70	1133	13.69	0.51	0.81	1173	1.13	0.68	0.39	1213	18.44	0.65	0.85
	First 30	1134	10.31	0.5	1.01	1174	2.2	0.36	0.47	1214	13.99	0.64	1.64
	Last 30	1135	8.36	0.44	0.76	1175	2.3	0.57	0.77	1215	14.82	0.58	1.04
	Last 70	1136	9.83	0.49	0.01	1176	2.35	0.62	0.44	1216	19.21	0.59	0.38
ip9	First 70	1137	13.95	0.49	0.86	1177	0.95	0.76	0.35	1217	18.41	0.65	0.87
	First 30	1138	9.79	0.55	0.78	1178	1.94	0.5	0.38	1218	13.8	0.65	1.18
	Last 30	1139	8.6	0.4	0.95	1179	2.26	0.59	0.77	1219	13.1	0.67	2.14
	Last 70	1140	9.93	0.46	0.01	1180	2.15	0.69	0.51	1220	17.54	0.66	0.57
ip10	First 70	1141	13.62	0.52	0.81	1181	1.04	0.72	0.38	1221	18.48	0.65	0.9
	First 30	1142	10.28	0.51	1.01	1182	2.42	0.23	0.61	1222	14.18	0.63	1.81
	Last 30	1143	8.46	0.42	0.8	1183	2.3	0.58	0.84	1223	14.62	0.59	1.46
	Last 70	1144	9.71	0.48	0.01	1184	2.39	0.61	0.58	1224	18.8	0.61	0.55

Table 16
Budhwad results with AMI.

Model No.	Training Percentage	Month/Input	RMSE	CE	MARE
1225	First 70	June Rt-1, Rt, Qt	22.65	-0.07	1.36
1226	First 30		15.6	0.06	3.6
1227	Last 30		9.36	0.48	1.74
1228	Last 70		12.64	0.47	0.19
1229	First 70	July Rt-2, Rt-1, R_t, Q_{t-1}, Q_t	24.19	0.67	0.65
1230	First 30		19.27	0.65	0.85
1231	Last 30		17.76	0.65	1.77
1232	Last 70		24.82	0.6	0.05
1233	First 70	August Rt-1, Rt, Qt	19.55	0.75	0.81
1234	First 30		18.26	0.61	1.61
1235	Last 30		14.45	0.7	0.6
1236	Last 70		19.29	0.68	0.01
1237	First 70	September Rt-4,Rt-3, Rt-2,Rt-1, Rt,Qt-1,Qt	13.38	0.53	1.0859
1238	First 30		9.99	0.53	1.2069
1239	Last 30		6.69	0.66	0.7407
1240	Last 70		0.87	0.93	0.01
1241	First 70	October Rt-1, Rt, Qt-1,Qt	2.27	0.31	0.4338
1242	First 30		2.52	0.28	0.603
1243	Last 30		2.13	0.59	0.8936
1244	Last 70		1.59	0.79	0.28
1245	First 70	5 Monthly Rt-2, Rt-1 ,Rt, Qt-1, Qt	15.5	0.75	0.54
1246	First 30		12.83	0.71	0.96
1247	Last 30		12.19	0.72	1.21
1248	Last 70		14.82	0.76	0.11

For June the best model (model 1227) predicted discharge of 41.12 m^3/s against the maximum observed value of 97.16 m^3/s which was in testing (figure 8). The best model for July (model 1039) predicted 96.15 m^3/s against 199 m^3/s (not shown). The maximum value of discharge in calibration was220.13 m^3/s. For August the best model (model 1067) predicted discharge of 99.83 m^3/s against 259.03 m^3/s observed discharge which was in testing (not shown). For September model, the maximum value of discharge in calibration was 146.71 m^3/s. The best model (model 1119) predicted 43.55 m^3/s discharge against 112 m^3/s. Figure 9 shows hydrograph for the month of September. For 5 Monthly combined model, the best model (model 1247) predicted discharge of 99.88 m^3/s against 259.03 m^3/s(not shown) which was in testing data set.

For Budhwad October results are better as compared to all other months which is similar to Mandaleshwar and Nighoje wherein results of October were the best. The peak prediction was again poor as observed in earlier models. Statistical analysis of data shows that, 87 % values of discharge in data were in the range of 1.1 m^3/s to 100 m^3/s, 10.38 % m^3/s values of discharge were in the range of 0 to 1 m^3/s, and 1.96 % values of discharge were in the range of 101 m^3/s to 300 m^3/s with 0.66% above 300 m^3/s.

For all the three stations CE value was negative for some models. It is observed that when there is large variation between observed and predicted value, then the CE value is negative. If such values are omitted from model, then CE values are found to increase indicating better prediction capacity.

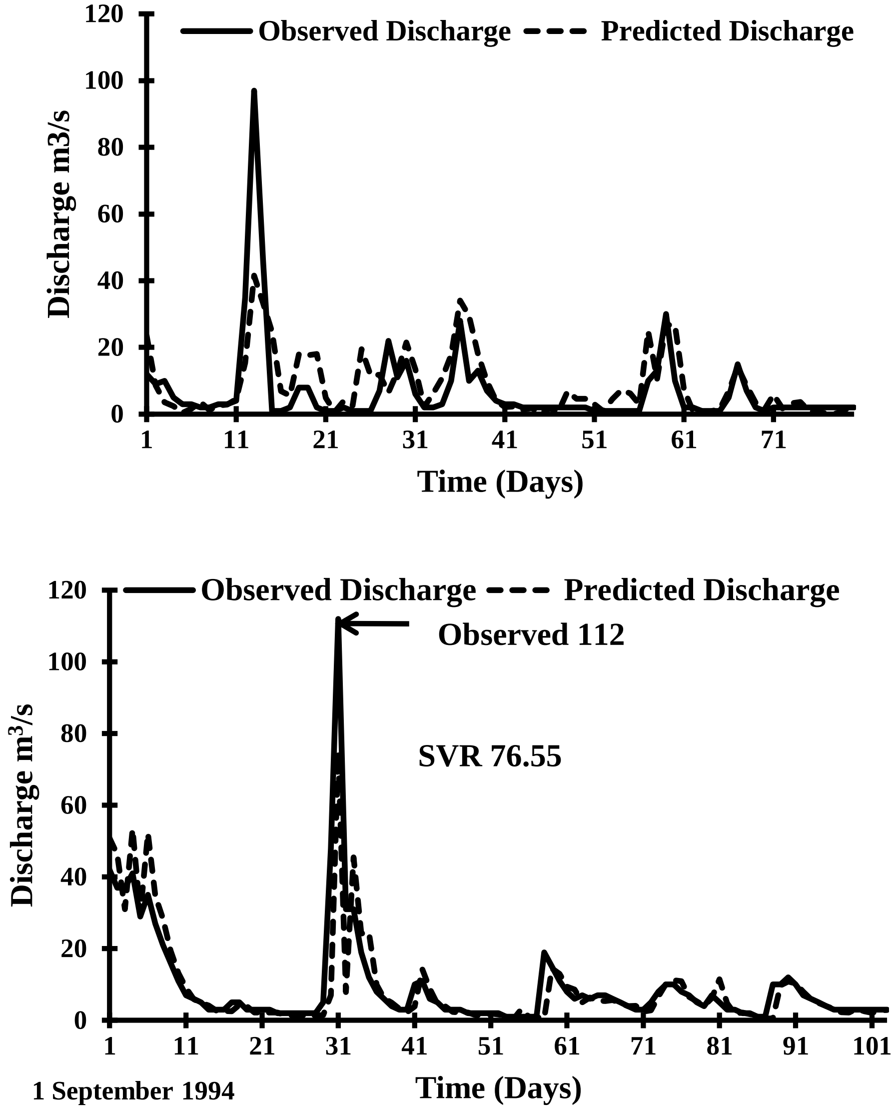


Fig. 9. Budhwad September last 70% calibration with AMI method of input selection.

6. Conclusion

In the present study stream flow forecasting for one day in advance was carried out at three locations namely Mandalaeshwar, Nighoje and Budhawad in India using three input selection methods namely Trial and Error, Correlation analysis, Average Mutual Information and the data-driven technique of support vector regression (SVR). Total 1248 models were developed with different combinations of input selection methods, data division and Kernels in SVR. All the models performed reasonably well in testing with a few exceptions. It can be said that AMI is a better method for input selection compared to trial and error and correlation analysis as evident from better Root Mean Square Error values at Mandaleshwar and Budhwad. At Nighoje method of trial and error seems to be the winner. Thus among the three input selection methods Trial and Error and Average Mutual Information seems to be superior as compared to correlation analysis in dealing with nonlinear problems like the one presented here. Comparison of RBF kernel, Linear Kernel, and Polynomial kernel showed that RBF kernel is the best as far as accuracy of prediction is concerned. Different data division combinations did not gave an exact insight for a most favorable combination of data division. This still remains an eluding problem. In all the models the October models at each location were the best at that particular location perhaps due to less variation in data. The major drawback of the models is poor prediction at peaks. This may be due to large variation in data and large difference in high and low values.

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