

# Hydrologic Design of Soil and Water Conservation Structures Using Probability Analysis and Machine Learning Techniques

## ABSTRACT

The soil and water conservation structures are constructed to overcome water scarcity as a result of interannual rainfall variability and paucity of the perennial source of water. A study was conducted to estimate the design runoff for the efficient hydrologic design of various soil and water conservation structures using Annual One Day Maximum Rainfall (ADMR) for the Saurashtra Region of Gujarat, India. The design rainfall at various return periods was predicted using three techniques *i.e.* probability distribution fitting, Artificial Neural Network (ANN) and Gaussian Process Regression (GPR) for 11 stations. Various goodness of fit tests revealed that ADMR was efficiently predicted by log-logistic (3P) distribution for six stations, generalized extreme value distribution for two stations and lognormal (3P), gamma (3P) and lognormal distribution for one station each. Among ANN and GPR, the performance indicators revealed that GPR has shown a higher capability to predict ADMR as compared to ANN with correlation coefficient ranging from 0.97 to 0.99, mean absolute error from 15 mm to 411 mm and root mean squared error from 40 mm to 494 mm for various stations. The design runoff estimation was demonstrated based on predicted ADMR for various soil and water conservation structures using SCS-Curve Number method for curve number 70 and 85. The study is useful for researchers, planners and engineers to implement the economical, efficient and safe design of various soil and water conservation structures.

**Key words:** *Annual one-day maximum rainfall; Artificial Neural Network; Gaussian Process; Probability distribution; Runoff estimation*

## Introduction

The efficient harvesting and conservation of water is a prominent feature for sustainable development of agriculture, climate change resilience and coping with inter-annual precipitation variability (Bitterman *et al.*, 2016; Gandhi and Patel, 2019). Harvested rainwater is not only useful in dry spells during *the Kharif* season but also for early sowing of *Rabi* crops (Singh *et al.*, 2019). The complete design of soil and water conservation structures can be split into three sections *i.e.* Hydrological Design, Hydraulic Design and Structural Design. The general guidelines are inadequate for executing such designs due to their

location-specific nature (Singh and Singh, 2017). The hydrologic design includes design runoff estimation from expected rainfall at a specific recurrence interval. While an over-designed structure results in an uneconomical design along with wastage of area towards construction, underestimated structure possesses a risk of failure, not conserving desired runoff and causing soil erosion in downstream areas (Gundalia, 2016; Otim *et al.*, 2019)

The duration of rainstorms in semi-arid regions rarely exceeds one day. Therefore, the annual one-day maximum rainfall (ADMR) is critical for designing soil and water conservation structures. The expected ADMR at various return periods were estimated by fitting various probability distributions e.g. normal, log normal, log pearson type-III, log-logistic, gamma, generalized extreme value, etc. to observed rainfall and location-specific best-fit models were selected (Gebremedhin *et al.*, 2017; Dhupal and Swain, 2020). However, Nahvi, *et al.*, (2018) favored the requirement of advanced and more reliable computational and simulation methods to model nonlinear and complex phenomena of precipitation. Machine learning techniques like Artificial Neural Networks (ANNs) and Gaussian process regression (GPR) can be proven useful to model complex hydrological processes including rainfall-runoff modeling and precipitation.

Abundant evidence is available for the successful prediction of rainfall/runoff using ANN. (Darji *et al.*, 2015). Gaussian process regression (GPR) is another non-parametric supervised machine learning method to model complex natural phenomena including rainfall (Ghasemi *et al.*; 2021). The GPR outperformed ANN for predicting various metrological and hydrological quantities including rainfall (Chang and Chen, 2018;Ghasemi *et al.*, 2021). Mishra and Kushwaha (2019) developed a model to predict rainfall using Gaussian process regression as a classifier with 95.4% accuracy at Raipur, India. Several methods are available to estimate runoff from rainfall however, United States Soil Conservation Service-Curve Number (SCS-CN) (USDA-SCS, 1986) is widely used due to quick and accurate runoff estimation, simplicity, robustness and acceptability and integration of various parameters in one number i.e. Curve Number. (Singh and Singh, 2017; Gandhi and Patel, 2019; Otim *et al.*, 2019). The past and recently developed popular hydrological models incorporated SCS-CN method for runoff estimation (Paola De *et al.*, 2013).

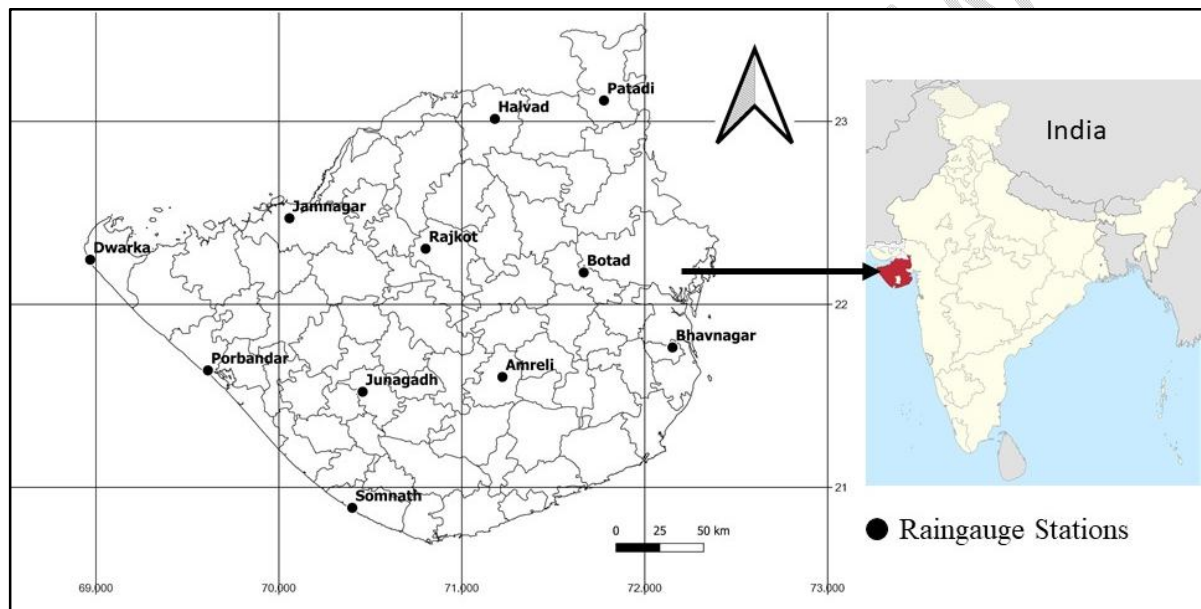
The present study was carried out in the Saurashtra region of Gujarat state (India), a semi-arid region with high dependence on rainfall, scarce perennial water resources with peculiar landform characteristics making the modeling of runoff generation challenging (Patel *et al.*, 2020). Keeping in view the facts mentioned above, a study was planned to

estimate design runoff for various soil and water conservation structures based on annual one-day rainfall using probability distribution fitting as well as artificial neural network (ANN) and gaussian processes regression (GPR).

## Materials and Methods

### Study Area and Rainfall Data

The present study was conducted for the Saurashtra region of Gujarat India), a semi-arid region located in western India between 20°30' to 23° N latitude and 69° to 72° E longitude (Fig.1).



**Fig. 1.** Study area and location of rain gauge stations

The average annual rainfall over different parts of the region varies widely from 400 to 900 mm. The duration of the rainy season lies between the middle of June to September. The rainfall distribution is uneven and irregular as the region is situated southwest monsoon periphery (Pandya *et al.* 2020). Saurashtra faces high dependence on groundwater along with the absence of major perennial rivers/streams and recurrent drought-like conditions (Saha *et al.*, 2017; Patel *et al.*, 2020). The daily rainfall data of one station in each of the 11 districts of Saurashtra as shown in Fig. 1 for the year 1981 to 2020 (40 years) were used to obtain a series of data sets of annual one-day maximum rainfall (ADMR) for estimating runoff.

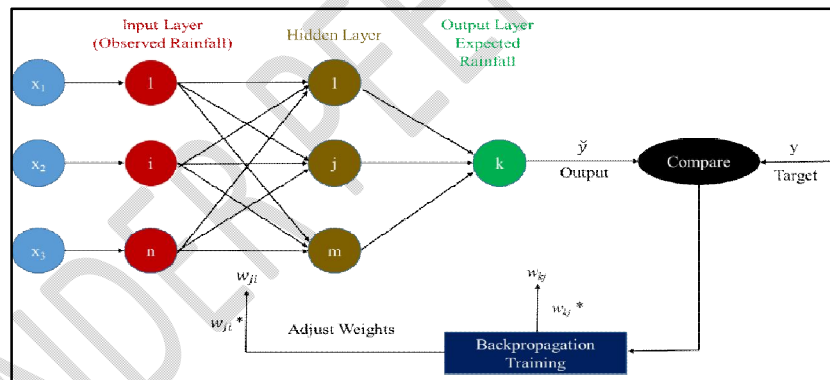
### Probability Distribution Fitting of ADMR

The observed return period of ADMR was calculated by Weibull's plotting position formula (Chow, 1964) and used by Dhupal and Swain (2020). Various nine probability

distributions *i.e.* Gamma, Gamma 3 Parameter, Generalized Extreme Value, Log-Logistic, Log-Logistic 3 Parameter, Log-Pearson 3 type, Lognormal, Lognormal (3P) and Normal distribution were fitted to ADMR. The description of various probability distribution functions is available explained by Sharma and Singh (2010). The distributions were subjected to three goodness of fit tests *i.e.* Chi-square test, Kolmogorov-Smirnov (K-S) test and Anderson-Darling (A-D) test to find the best fit distribution for each of 11 stations which are discussed in Mandal and Choudhury, 2014 and Singh *et al.* 2018. The best-fit distribution was decided based on the method of ranking distributions by assigning a score from 1 to 9 with distribution having the lowest test statistic value as score 9, second-lowest as 8 and so on. Scores for all three tests were summed up and the distribution with the highest combined score was designated as best-fit (Olofintoye *et al.*, 2009).

### Artificial Neural Network (ANN)

Among various ANN models, multi-layer perceptron neural network model (MLP) trained with feed-forward backpropagation algorithm widely used for hydro-meteorological study including rainfall. The architecture of MLP is characterized by the activation function used in each input, hidden and output layer as illustrated in Fig. 2.



**Fig. 2.** MLP feed-forward ANN with backpropagation

With  $X_i$  is input *i.e.* observed rainfall at various return periods, 1 to n are neurons of an input layer, 1 to m are neurons of the hidden layer, k is output neuron and Y is output *i.e.* expected rainfall,  $w_{ji}$  and  $w_{kj}$  are weights connected hidden & input layers and output & hidden layer. The parameters used during the training of the network are learning rate, Momentum, Number of Neurons, error and Number of Epochs.

### Gaussian Processes Regression (GPR)

The gaussian process is associated with Gaussian probability distribution, which describes random variables. The Gaussian process of  $f(x)$  is defined by covariance, mean  $m(x)$  functions that are a matrix and a vector, respectively, and expresses the distribution between functions. The covariance function leads to the creation of functions with different degrees or the different types of continuous structures and provides the possibility to choose the right selection. The method Matern covariance function can be used in a majority of which requires specification of only the covariance structure (Chang and Chen, 2018). The covariance matrix is required to be a semi-positive definite matrix, and the kernel functions fulfill these requirements so they are used to obtain the covariance matrix. The present study incorporated the target response variable as ADMR at various return periods using observed ADMR.

The set of random variables is created which is evaluated at  $x$  by GP  $f(x)$  where GP is a distribution over functions, *i.e.*,

$$f(x) \sim \text{GP}(m(x), k(x, x^T))$$

Here,  $m(x) = E[f(x)]$  is mean function and  $k(x, x^T) = E[(f(x) - m(x))(f(x^T) - m(x^T))]$  is covariance kernel. The  $x = (x_1, \dots, x_n)^T$  is the function's index, and  $f(x) = (f_1, \dots, f_n)^T$  is the function's output, *i.e.*,  $(x_i, f_i)$  is a point in  $R^2$ . The present study considered common GP, and kernel which is defined with mean function 0 and squared exponential (SE) covariance function

$$k(x_i, x_j) = \sigma^2 \exp\left\{-\frac{1}{2l^2}(x_i - x_j)^2\right\}$$

Where  $\sigma^2$  and  $l$  are hyper-parameters that control the shape of the process; especially,  $\sigma^2$  controls the amount of variation in  $f(x)$  and  $l$ , the length-scale parameter, controls the correlation. Several options are available for kernel, however, SE kernel is widely used in GPR (Rasmussen, 2005). The height and amplitude of GP with SE covariance kernel is controlled by  $\sigma^2$  and  $l$  controls the correlation between observations. The covariance matrix  $K$  in a multivariate normal distribution is constructed by the kernel as below.

$$K = \begin{pmatrix} k(x_1, x_1) & \cdots & k(x_1, x_n) \\ \vdots & \ddots & \vdots \\ k(x_n, x_1) & \cdots & k(x_n, x_n) \end{pmatrix}$$

The finite number  $n$  of realizations  $x = (x_1, \dots, x_n)^T$ , and corresponding  $y = (y_1, \dots, y_n)^T$ , where  $y \triangleq f(x)$  is observed. The vector  $x$  is commonly called the input and represents the location of the process, *i.e.*, observation  $y_i = f(x_i)$ . The vector  $y$  is referred to

as the output and is the function evaluated at location  $x$ . The generalization to a multivariate normal distribution is done with  $f(x) \sim N(0, K)$ . This is possible because marginalizing a Gaussian distribution is trivial: the resulting distribution is Gaussian and we can ignore the ( $x$  and  $y$ ) pairs that are unobserved or missing (Forrest and McNicholas, 2020). The hyper-parameters are often estimated to maximize the likelihood of the GP. The detailed expressions and calculations are available in Rasmussen and Williams (2006).

The ANN and GPR were performed using Weka (Waikato Environment for Knowledge Analysis) machine learning tool developed at the University of Waikato, New Zealand. The detailed calculation steps can be available by Frank *et al.* 2016. The performance of developed ANN and GPR in terms of rainfall prediction was tested using the coefficient of determination ( $R^2$ ), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE).

### **Return Period for Various Soil and Water Conservation Structures**

The return periods of different soil and water conservation structures based on their respective annual one-day maximum rainfall data are 5 years for field bunding, 10 years for terrace outlets and vegetative outlets, 15 years for field diversion, 10 to 15 years for small permanent masonry gully control structures, 25 years for check dams, drainage-line treatment structures, stock water dams, 25 to 50 years for earthen storage dams with natural spillways and 50 to 100 for storage and diversion dams having spillways (Sharma *et al.*, 2015 and Dhupal and Swain, 2020). The ADMR for these return periods was evaluated and tabulated.

### **Runoff Estimation**

Various studies have been conducted to estimate runoff by the SCS Curve number method at various locations, river basins and watersheds in the Saurashtra with curve numbers varying from 68 to 85 for different land use characteristics (Patel *et al.*, 2012; Sonagara *et al.* 2015; Parmar *et al.*, 2016 and Gandhi; Patel 2019). Based on these facts, the design runoff was estimated for various soil and water conservation structures using two curve number values i.e. 70 and 85 for demonstrating the idea.

## **Results and Discussions**

### **ADMR Based on Probability Distribution Fitting**

The average annual rainfall based on rainfall data from 1981 to 2020 for various stations under the study ranges from a minimum of 467 mm for Morbi and a maximum of 985 mm for Junagadh. The descriptive statistics of ADMR for 11 stations of Saurashtra are

given in Table 1. It can be observed that the maximum average ADMR was 167 mm for Junagadh followed by 162 mm for Gir Somnath. While minimum average ADMR was observed as 96 mm for Botad. In most the cases, a higher average extreme rainfall event corresponds to higher variability and hence higher CV%, which is evident from Table 1. Gebremedhin *et al.* (2017) also confirmed this fact during a study on probable maximum precipitation (PMP) for Ethiopia.

**Table 1.** Statistical Analysis of Annual One Day Maximum Rainfall (ADMR)

Station	AM, mm	SD, mm	CV%	C <sub>S</sub>	C <sub>K</sub>
Amreli	110	70	64	1.40	1.25
Bhavnagar	103	56	54	1.06	1.56
Botad	96	45	46	0.97	0.51
Dwarka	112	77	69	1.30	1.75
Gir Somnath	162	107	66	2.31	7.51
Jamnagar	146	95	65	1.14	1.26
Junagadh	167	152	91	4.87	27.68
Morbi	98	47	48	0.79	-0.16
Porbandar	145	122	84	2.99	12.19
Rajkot	120	61	51	1.34	2.28
Surendranagar	107	48	45	0.81	0.13

AM= Arithmetic mean, SD= Standard deviation, CV=Coefficient of variation, C<sub>S</sub> = Coefficient of skewness, C<sub>K</sub> = Coefficient of kurtosis

The observed ADMR for return period 1.025 to 41 based on 40 years of data was subjected to various nine probability distributions. Table 2 depicts the best-fit probability distribution for various stations based on the total score of three goodness of fit tests *i.e.* Kolmogorov-Smirnov (K-S), Anderson-Darling (A-D) and Chi-square test. Out of 11 stations, log-logistic (3P) was found to be the best fit to predict ADMR for the majority of stations (Amreli, Bhavnagar, Botad, Junagadh, Porbandar and Rajkot). During the study in the semi-arid zone of Northwest India, Kumar *et al.* (2018) revealed that each distribution has its pros & cons and one cannot fit in all locations, so examination of best-fit models owing to its peculiar location is essential. Similar here also generalized extreme value distribution was found best-fit two stations *i.e.* Gir Somnath and Jamnagar, lognormal (3P), gamma (3P) and lognormal for one station each. The distributions found to be reliable to predict ADMR were

also shown capability to estimate ADMR across India (Babu *et al.*, 2006; Sharma and Singh, 2010; Mandal and Choudhury 2014; Kumar *et al.*, 2018; Dhupal and Swain 2020).

**Table 2.** Best fit distribution for ADMR

District	Best-Fit Distribution
Amreli Bhavnagar Botad Dwarka Junagadh Porbandar Rajkot	Log-Logistic (3P)
Gir-Somnath	Gen. Ext. Value
Jamnagar	Gen. Ext. Value
Morbi	Gamma (3P)
Surendranagar	Lognormal

The best fit probability distribution for Junagadh and Rajkot obtained a full score of 27, which reveals that all three tests showed the same probability distribution as the best fit. Except for Morbi, all the remaining 10 stations observed 24 or more score for best-fit probability distributions out of a maximum possible 27, which suggests that obtained best-fit probability distributions were found appropriate by all three goodness of fit tests to predict ADMR. Table 2 also depicts the parameters of best-fit distribution for each station, which represent essential properties of location, scale and shape of a distribution required to predict the expected values. Similarly, in the present study also, a single distribution could not emerge as the best fit for all locations.

#### ADMR Based on ANN and GPR

The performance of ANN and GPR was evaluated in the testing phase to predict the ADMR for various return periods based on correlation coefficient, mean absolute error and root mean squared error (Table 3).

**Table 3** Performance of Gaussian Regression Process (GPR) and ANN

Station	Correlation		Mean Absolute		Root Mean Square	
	Coefficient		Error, mm		Error, mm	
	GPR	ANN	GPR	ANN	GPR	ANN
Amreli	0.99	0.52	192	202	213	212
Bhavnagar	0.99	0.52	161	183	174	191

Botad	0.99	0.47	134	135	141	141
Dwarka	0.97	0.55	15	229	21	241
Gir Somnath	0.97	0.50	322	358	369	389
Jamnagar	0.99	0.97	35	293	40	304
Junagadh	0.99	0.45	411	466	494	670
Morbi	0.99	0.86	136	138	143	144
Porbandar	0.99	0.52	337	371	401	420
Rajkot	0.99	0.78	190	203	206	212
Surendranagar	0.99	0.47	148	141	155	148

The higher correlation coefficient between observed and predicted rainfall ranging from 0.97 to 0.99 for GPR was observed as compared to ANN (0.45 to 0.86). The mean absolute error in rainfall prediction was lower i.e. from 15 to 411 mm for GPR i.e. as compared to ANN (135 to 466 mm) for various stations. Among all stations, only Surendranagar was observed with lower MAE in ANN (142 mm) as compared to GPR (148 mm). While RMSE value of GPR and ANN for stations Amreli, Botad, Morbi, Rajkot and Surendranagar was very close to each other with the difference being less than 10 mm. The difference in RMSE between GPR and ANN was low i.e. 16 to 20 mm for Bhavnagar, Gir Somnath and Porbandar while for Dwarka, Junagadh and Jamnagar it was as high as 175 to 219 mm. These findings are also supported by a study by Sahraei *et al.* (2021) disclosing that ANN underestimated the events with high maximum values and overestimated the events with low maximum values. Hence, considering all three performance indicators i.e. correlation coefficient, mean absolute error and root mean square error, GPR performed better than ANN to predict the ADMR for various stations. Sudheer *et al.* (2003) during the study of river flow simulation reported that ANN models suffer from the weakness in predicting extreme events unless they are trained by similar extreme events. As in the present case also, the observed values of rainfall obtained using Weibull's plotting position was ranging from 1.025 years to a maximum of 41 years, but expected rainfall for 50 and 100 years return period was also evaluated. Another reason to point out is characteristics "sigmoidal" function of ANN are to be bounded and increase monotonically to the variability induced by extreme values. On the contrary, the parsimonious structure of GPR does not allow overfitting in such cases (Chang and Chen, 2018). The ANN might perform better in this case if data of more than 40 years are used for the analysis. Mishra and Kushwaha (2019)

also observed the satisfactory performance of the Gaussian process regression model in precipitation forecasting. Hence, considering the superiority of GPR over ANN the runoff was also estimated by ADMR obtained from GPR along with best fir distribution.

### Runoff Estimation Using ADMR

The expected ADMR for various return periods based on best-fit probability distribution and GPR is given in Table 4.

**Table. 4** Design Rainfall for Various Return Periods (mm)

Station	Method	5	10	15	25	50	100
Amreli	PBF	143	201	247	315	443	625
	GPR	126	147	167	207	308	510
Bhavnagar	PDF	140	175	196	226	271	324
	GPR	116	132	147	179	259	417
Botad	PDF	130	154	173	198	238	286
	GPR	106	118	130	155	216	338
Dwarka	PDF	163	211	241	277	328	381
	GPR	130	153	175	220	332	557
Gir Somnath	PDF	214	281	326	386	481	592
	GPR	189	224	258	328	501	847
Jamnagar	PDF	209	268	306	353	419	490
	GPR	167	194	221	274	409	677
Junagadh	PDF	206	255	288	331	398	477
	GPR	207	257	307	407	656	1156
Morbi	PDF	133	163	180	201	227	253
	GPR	108	120	132	157	217	339
Porbandar	PDF	194	264	313	381	498	649
	GPR	177	218	258	339	541	946
Rajkot	PDF	157	197	223	258	315	383
	GPR	134	152	170	206	297	477
Surendranagar	PDF	142	173	192	215	247	279
	GPR	117	130	142	168	231	358

PDF:- Probability distribution fitting

The design rainfall based on GPR for 5, 10, 15 and 25 years return period was found less as compared to that of the best-fitted probability distribution for all the stations except Junagadh. For 50 years return period, Dwarka, Gir-Somnath, Junagadh, Morbi and Porbandar observed a higher value of expected rainfall for GPR as compared to that of best-fit distribution fittings. While for 100 years return period, the rainfall by GPR was found higher

than by best-fit probability distribution for all districts except Amreli. Junagadh was the only station for which rainfall predicted by GPR was higher than by probability distribution for all the six return periods considered. The observed average ADMR based on 40 years of data was highest for Junagadh as compared to all the districts (167 mm), in the case of 100 years return periods, expected rainfall was naturally on the higher side. For such higher rainfall values, the difference between the expected value by a probability distribution and GPR was also high as compared to that of lower return periods. Thus, it can be interpreted that for higher observed ADMR events and higher return periods, GPR estimates are higher as compared to probability distribution and vice-versa. The estimated ADMR for various return periods serves as input for the hydrologic design of different soil and water conservation structures. Babu *et al.* 2006 demonstrated the capability of ADMR for the efficient design of a masonry check dam in Bankura district of West Bengal based on probability distribution fitting.

The design runoff was estimated for various soil and water conservation structures using two curve number values i.e. 70 and 85 (Table 5 and Table 6). However, runoff can be estimated using any curve number by using ADMR in Table 4. The expected runoff for filed bunding based on best-fit distribution was ranging from a minimum 54 mm (Botad) to 123 mm (Gir Somnath) for CN70 and from 88 mm (Botad) to 168 mm (Gir Somnath) for CN85. Considering GPR, the expected runoff was ranging from 46 mm (Botad) to 131 mm (Junagadh) for CN70 and from 66 mm (Botad) to 161 mm (Junagadh) for CN85. Similarly for Storage and Diversion Dams having spillways considering 100 years return period, the expected runoff based on best-fit distribution was ranging from a minimum 157 mm (Morbi) to 534 mm (Porbandar) for CN70 and from 206 mm (Morbi) to 590 mm (Porbandar) for CN85. Considering GPR, the expected runoff was ranging from 254 mm (Botad) to 1060 mm (Junagadh) for CN70 and from 290 mm (Botad) to 1103 mm (Junagadh) for CN85 for Storage and Diversion Dams having spillways. The design runoff for structures like Terrace outlets and vegetative outlets, Field diversion, Small permanent masonry gully control structures, Check Dams, Drainage-line treatment Structures (DTS), Stock Water Dams and Earthen Storage Dams with Natural Spillways can also be observed in Table 5 and 6.

**Table. 5** Estimated Runoff for 5, 10 and 15 Years Return Period (mm)

Station	RP 5 Years		RP 10 Years		RP 15 Years	
	CN70	CN85	CN70	CN85	CN70	CN85

	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Amreli	64	62	100	85	112	78	156	104	151	96	200	123
Bhavnagar	61	53	97	75	89	66	130	90	107	79	151	105
Botad	54	46	88	66	72	55	110	77	88	65	129	89
Dwarka	80	65	119	89	120	84	165	110	147	103	194	131
Gir Somnath	123	115	168	144	183	147	234	178	224	179	278	211
Jamnagar	118	96	163	123	171	120	221	149	206	144	258	175
Junagadh	115	131	160	161	159	177	208	210	189	224	240	259
Morbi	56	47	91	68	80	57	119	79	94	66	136	90
Porbandar	106	105	149	133	167	141	216	172	212	178	265	211
Rajkot	75	68	114	92	108	83	152	109	131	99	177	126
Surendranagar	63	54	100	76	88	64	129	88	104	75	147	100

(1) based on best-fit distribution, (2) based on GPR

**Table 6.** Estimated Runoff for 25, 50 and 100 Years Returns Period (mm)

Station	RP 25 Years				RP 50 Years				RP 100 Years			
	70		85		70		85		70		85	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Amreli	214	132	267	162	335	225	393	260	511	421	574	460
Bhavnagar	133	107	180	135	174	179	224	212	222	330	276	368
Botad	109	85	153	111	144	139	192	170	187	254	238	289
Dwarka	179	143	230	174	226	249	280	284	276	467	332	506
Gir Somnath	280	244	337	279	371	412	431	451	479	753	541	795
Jamnagar	249	194	304	227	312	322	370	359	380	585	440	626
Junagadh	229	320	283	357	292	564	349	605	367	1060	427	1103
Morbi	111	87	155	113	134	141	181	172	157	255	206	291
Porbandar	276	255	332	291	388	451	448	491	535	851	598	894
Rajkot	162	131	211	161	214	215	267	249	278	389	334	427
Surendranagar	123	96	169	124	151	154	200	185	181	274	232	310

(1) based on best-fit distribution, (2) based on GPR

From the economical design point of view, among expected runoff by probability distribution function and GPR, the lower of the two values should be considered for the structure design. However, in the situation where finance is not much constraint, the higher of

the two can be used. This study has demonstrated the potential of machine learning technique like the Gaussian Regression Process (GPR) in addition to probability distribution fitting to standardize the hydrologic design of various structures for a particular region using ADMR. The study can serve as a ready reckoner for design engineers, planners and policymakers for efficient and economic structure design as well as working out cost economics for various soil and water conservation interventions during project proposal preparation. The replication of such study in a region would help in planning, designing and management of different types of hydraulic structures for effective utilization of available water resources.

## Conclusions

The probability distribution fitting of ADMR revealed that out of 11 stations, log-logistic (3P) was found best-fit for 6 stations, generalized extreme value distribution for two stations and lognormal (3P), gamma (3P) and lognormal for one station each. The GPR has shown superior performance to predict ADMR at various return periods as compared to ANN based on correlation coefficient, mean absolute error and root mean squared error. The expected ADMR based on GPR and best-fit distribution was evaluated for various structures incorporating return periods 5 to 100 years. The design runoff estimation for CN 70 and CN85 for various soil and water conservation structures using GPR and probability distributions was demonstrated. The study will be useful to formulate the efficient and economic design of various soil and water conservation structures and help in utilizing the available rain and land resource to their potential.

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