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Hydrologic Design of Soil and Water Conservation Structures Using Probability Analysis and Machine Learning Techniques in Saurashtra Region of Gujarat, India

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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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. The present study was aimed to estimate the design runoff for the efficient hydrologic design of various soils and water conservation structures using machine techniques for enabling efficient harvesting of available rainfall with economical design which can support in developing climate resilience for the Saurashtra region of Gujarat, India. The design rainfall at various return periods was predicted by Annual One Day Maximum Rainfall (ADMR) using three technics *i.e.* Probability Distribution Fitting,

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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 return periods suitable for various soil and water conservation structures like field bunding, terrace outlets and vegetative outlets, field diversion, permanent masonry gully control structures, earthen dam, etc. 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.

Keywords: Annual one-day maximum rainfall; artificial neural network; Gaussian process; probability distribution; runoff estimation.

1. INTRODUCTION

Water is one of the most essential components for survival of the life on the earth. The Indian subcontinent is facing the problems of ever-growing population and increasing urbanization which have led to increasing the demand of water for agriculture, industry and domestic use. The rise in temperature will occur owing to climate change which will cause spatial and temporal variations in depth, intensity and frequency of rainfall [1]. Soil and water conservation structures possess the benefits such as increased water availability agriculture and livestock, conservation of potentially productive land through reduced soil erosion, reduced nutrient loss from the soil, and environment conservation [2]. Implementing suitable water harvesting helps the mitigation against meteorological and agricultural droughts [3].

Runoff plays an essential part in the hydrological cycle for resolving water quality and quantity issues like flood predictions and ecological and biological connections in the aquatic environment [4]. Hydrologists have been attempting to understand the translation of rainfall to runoff for many years to estimate stream flow for objectives including water supply, flood control, irrigation, drainage, water quality, power production, recreation, and fish and wildlife propagation [2]. Runoff modelling is essential for better understanding the impact of all the changes on hydrological phenomena [5].

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 [6,7]. Harvested rainwater is not only useful in dry spells during *the Kharif* season but also for early sowing of *Rabi* crops [8]. 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 [9]. 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 [10,11].

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 [12,13]. However, Nahvi, et al., [14] 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 proved 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 [2,15-17]. Gaussian Process Regression (GPR) is another non-parametric supervised machine learning method to model complex natural phenomena including rainfall [18]. The GPR outperformed ANN for predicting various metrological and hydrological quantities including rainfall [18,19]. Mishra and Kushwaha [20] 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 [4] however, United States Soil Conservation Service-Curve Number (SCS-CN) [21] 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 [7,9,11]. The past and recently developed popular hydrological models incorporated SCS-CN method for runoff estimation [22].

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).

2. MATERIALS AND METHODS

2.1 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). The Saurashtra is a semi-arid region with high dependence on rainfall, scare perennial water resources with peculiar landform characteristics making the modeling of runoff generation challenging [23].

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 [24]. Saurashtra faces high dependence on groundwater along with the absence of major perennial rivers/streams and recurrent drought-like conditions [23,25]. The locations of rainguage station covering one station in daily rainfall data of one station in each of the 11 districts of Saurashtra as shown in Fig. 1. The daily rainfall data 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.

2.2 Probability Distribution Fitting of ADMR

The observed return period of ADMR was calculated by Weibull's plotting position formula [26] and used by Dhupal and Swain [13]. 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 [27]. 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, [28] and Singh et al. [29]. 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 [30]. The probability distribution fitting was carried out using easy-fit tool.

2.3 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.

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.

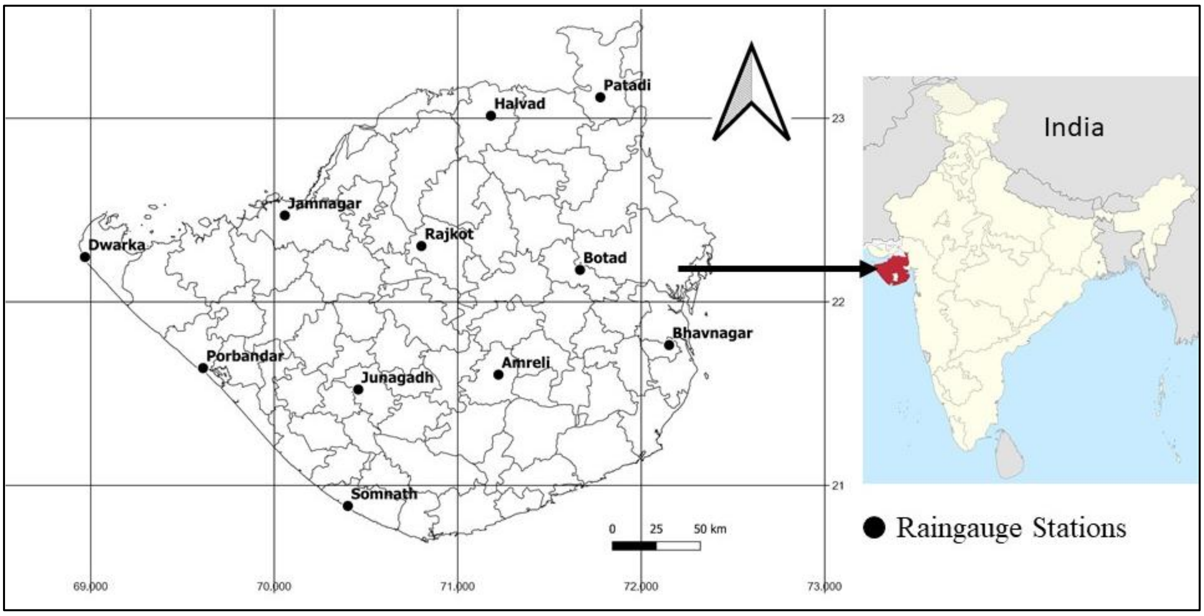

Fig. 1. Study area and location of rain gauge stations

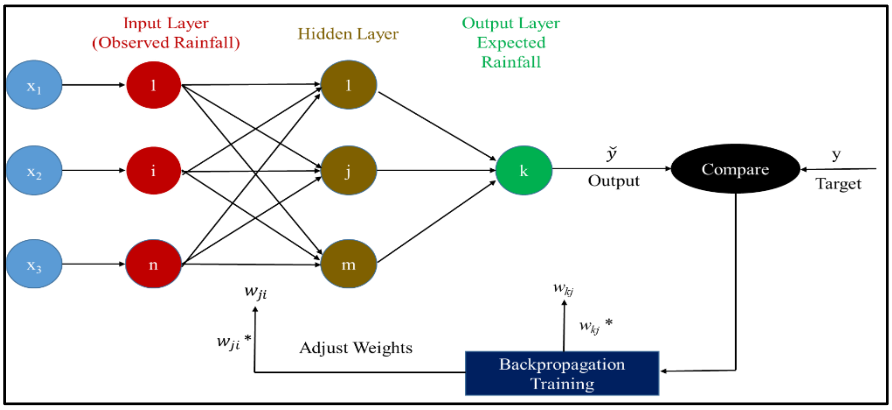

Fig. 2. MLP feed-forward ANN with backpropagation

2.4 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 [19]. 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.*

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

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 $x = (x_1......,x_n)^T$ is the function's index, and $f(x) = (f_1........,f_n)^T$ 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

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

Where σ^2 and l are hyper-parameters that control the shape of the process; especially, σ^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 [31]. The height and amplitude of GP with SE covariance kernel is controlled by σ^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 $x = (x_1 \ldots\ldots, x_n)^T$, and corresponding $y = (y_1 \ldots\ldots, y_n)^T$, 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 [32]. The hyper-parameters are often estimated to maximize the likelihood of the GP. The detailed expressions and calculations are available in Rasmussen and Williams [31].

The ANN and GPR were perfumed 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. [33]. 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).

2.5 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 [13,34]. The ADMR for these return periods was evaluated and tabulated.

2.6 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 [7,35-37]. 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.

3. RESULTS AND DISCUSSION

3.1 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. [12] also confirmed this fact during a study on probable maximum precipitation (PMP) for Ethiopia.

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 and parameters 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. [38] 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 [13,27,28,38,39].

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.

Table 1. Statistical analysis of ADMR

Station	AM(mm)	SD(mm)	CV%	C_S	C_K
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_S = Coefficient of skewness, C_K = Coefficient of kurtosis

Table 2. Test statistics and parameters of best fit distribution for ADMR

SN	District	Test statistics for best fit distribution					Parameters
		Best fit distribution	Kol. Smirn.	Ander. Darl.	Chi-Sq.	Score	
1	Amreli	Log-Logistic 3P)	0.09	0.38	1.30	26	α=1.9107 β=53.753 γ=31.647
2	Bhavnagar	Log-Logistic 3P)	0.09	0.25	0.63	25	α=4.3957 β=125.38 γ=-32.318
3	Botad	Log-Logistic 3P)	0.07	0.21	0.86	24	α=3.8922 β=88.207 γ=-1.2392
4	Dwarka	Lognormal (3P)	0.07	0.15	0.47	25	σ=0.50056 μ=4.8644 γ=-34.268
5	Gir-Somnath	Gen. Ext. Value	0.09	0.21	1.23	24	k=0.24014 σ=57.268 μ=110.92
6	Jamnagar	Gen. Ext. Value	0.07	0.29	0.29	26	k=0.09504 σ=67.835 μ=99.458
7	Junagadh	Log-Logistic 3P)	0.09	0.42	1.49	27	α=4.0468 β=159.64 γ=-19.174
8	Morbi	Gamma (3P)	0.06	0.20	0.64	22	α=2.7946 β=35.6 γ=20.412
9	Porbandar	Log-Logistic 3P)	0.09	0.36	1.73	26	α=2.6867 β=117.96 γ=-3.2577
10	Rajkot	Log-Logistic 3P)	0.07	0.17	0.08	27	α=3.5806 β=106.17 γ=0.83262
11	Suren. Nagar	Lognormal	0.07	0.28	1.68	25	σ=0.45688 μ=4.5697

3.2 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).

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. [40] 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. [41] 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 [19]. The ANN might perform better in this case if data of more than 40 years are used for the analysis. Mishra and Kushwaha [20] 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 fit distribution.

3.3 Runoff Estimation Using ADMR

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

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, 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.

Table 3. Performance of GPR and ANN

Station	Correlation coefficient		Mean absolute error, mm		Root mean square 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

Table 4. Design rainfall for various return periods (mm)

Station	Method	5	10	15	25	50	100
Amreli	PDF	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, GPR:- Gaussian Process Regression

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 corresponding to return periods as mentioned in section 2.5 using two curve number values i.e. 70 and 85 (Fig. 3 and Fig. 4). 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 corresponding to return periods as mentioned in section 2.5 based on estimated ADMR can be observed in Fig. 3 and Fig. 4.

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 technic 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.

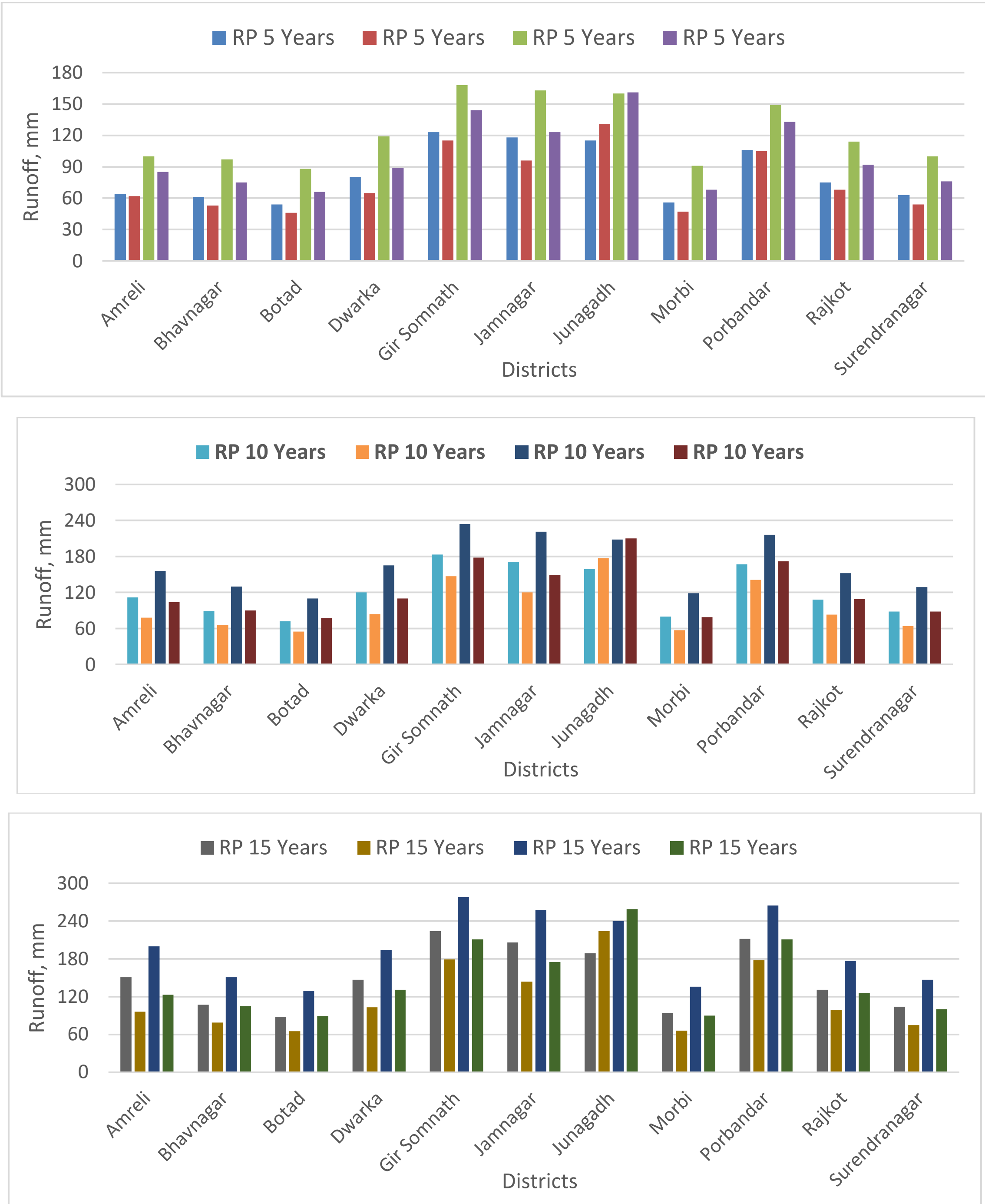

Fig 3. Estimated runoff for 5, 10 and 15 years return period, mm

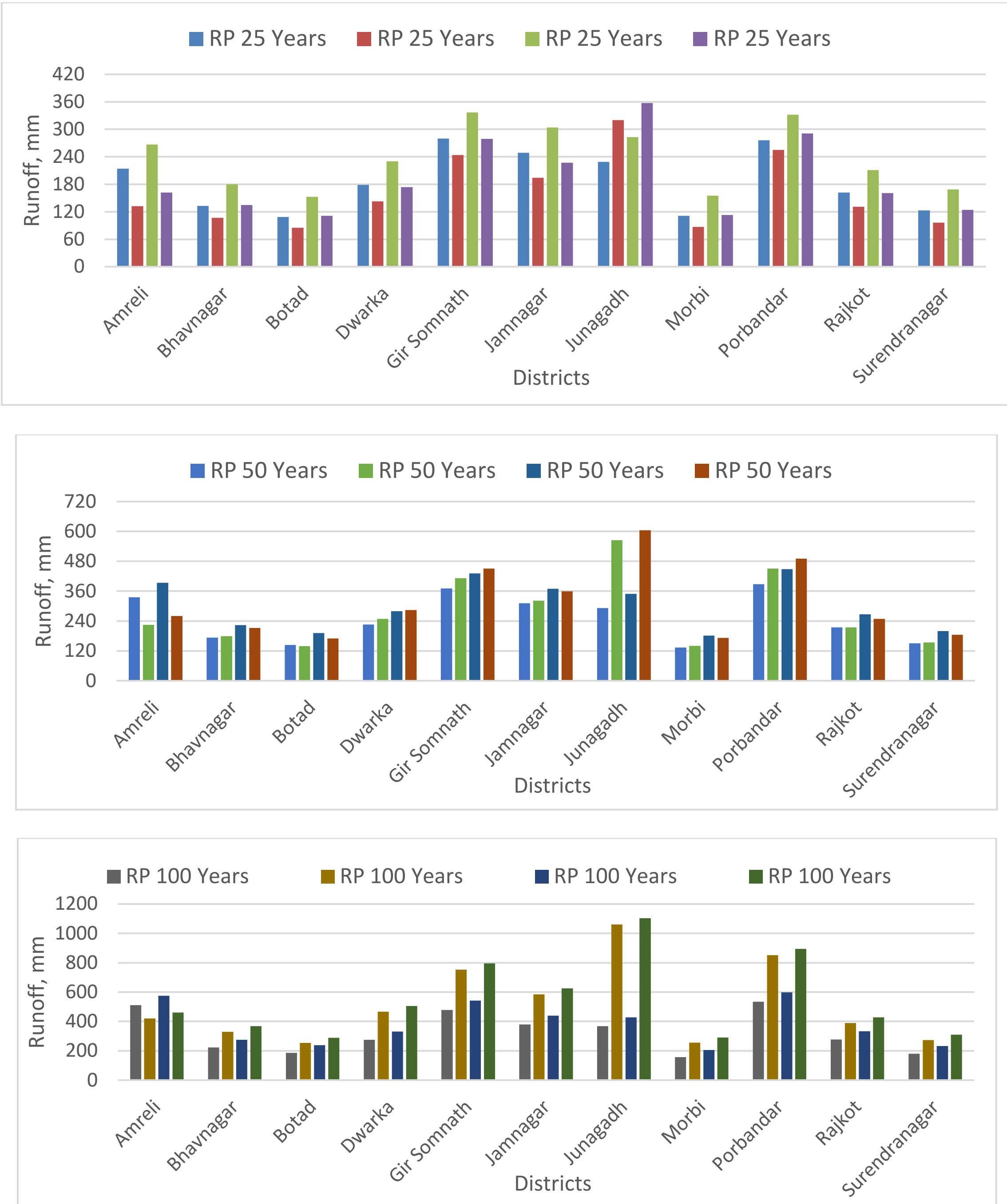

Fig. 4. Estimated runoff for 25, 50 and 100 years return period, mm

4. CONCLUSION

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 results from this 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.

CONFERENCE DISCLAIMER

Some part of this manuscript was previously presented in the conference: 3rd International Conference IAAHAS-2023 "Innovative Approaches in Agriculture, Horticulture & Allied Sciences" on March 29-31, 2023 in SGT University, Gurugram, India. Web Link of the proceeding: https://wikifarmer.com/event/iaahas-2023-innovative-approaches-in-agriculture-horticulture-allied-sciences/

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

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