Prediction of Seasonal and Annual Rainfall for Pune and Mahabaleshwar Regions using Multiple Linear Regression Models

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Correlation coefficient, Linear regression, Mean squared error, Model efficiency, Rainfall

ABSTRACT
Prediction of seasonal and annual rainfall for a river basin is of utmost importance for planning and design of irrigation and drainage systems as also for command area development. Since the distribution of rainfall varies over space and time, it is required to analyze the data covering long periods and recorded at various locations to arrive at reliable information for decision support. In this context, a study on prediction of seasonal (monsoon and post-monsoon) and annual rainfall for Pune and Mahabaleshwar using multiple linear regression (MLR) models viz., Regression Model-1 (RM1), Regression Model-2 (RM2) and Regression Model-3 (RM3) is carried out and the results are presented in this paper. The meteorological data such as rainfall (R), minimum temperature (Tmin), maximum temperature (Tmax), average wind speed (AWS) and relative humidity (RH) observed at Pune and Mahabaleshwar for the period 1997 to 2019 is used. The seasonal and annual series of meteorological data is extracted from the daily data and used for rainfall prediction by using MLRs, which are evaluated through correlation coefficient (CC), Nash-Sutcliffe model efficiency (NSE) and root mean squared error (RMSE). The study shows that the RMSE on predicted seasonal and annual rainfall using RM3 with all meteorological data (viz., R, Tmin, Tmax, AWS and RH) is minimum than those values of RM1 (with R, Tmin and Tmax) and RM2 (with R, Tmin, Tmax and AWS) for Pune and Mahabaleshwar. The study also shows that the NSE in rainfall prediction using RM3 is higher than those values given by RM1 and RM2. The CC values in seasonal and annual rainfall prediction using RM1, RM2 and RM3 vary from 0.906 to 0.973 for Pune while 0.963 to 0.987 for Mahabaleshwar. The paper presents the RM3 is better suited model for prediction of seasonal and annual rainfall for Pune and Mahabaleshwar.

1. INTRODUCTION

Knowledge of rainfall characteristics plays an important role in understanding hydrology of a region as well as for planning and management of water resources. Rainfall is one of the key natural resources that have a varying impact on human society such as agricultural activities, hydro-power generation, flood control and sustainability of biodiversity. Apart from this, rainfall prediction is needed for estimating the water requirement in a particular area or a region. Since the distribution of rainfall varies over space and time, it is required to analyze the data covering long periods and recorded at various locations to arrive at reliable information for decision support.

A wide range of rainfall forecast methods based on empirical and dynamical approaches are generally employed in weather prediction at regional and national levels (Cramer et al., 2017; Al Mamun et al., 2018; Anusha et al., 2019). The empirical approach is based on analysis of historical data of the rainfall and its relationship to a variety of atmospheric and oceanic variables over different parts of the world. The most widely used empirical approaches used for climate prediction are regression, artificial neural network, fuzzy logic and group method of data handling. In dynamical approach, predictions are generated by physical models based on systems of equations that predict the evolution of the global climate system in response to initial atmospheric conditions.

During the past, number of studies on rainfall prediction using Multiple Linear Regression (MLR) has been carried out by different researchers for various regions. Singhrattna et al. (2005) used MLR and non-parametric approach based on local polynomials with parameters such as sea-surface temperature, sea-level pressure, wind speed and EiNino Southern Oscillation Index (ENSO).

Chattopadhyay (2007) also indicated that the feed forward Artificial Neural Network (ANN) has less error than MLR in predicting the average summer monsoon rainfall over India. Dahamsheh and Aksoy (2009) suggested that the ANNs were slightly better than MLR in forecasting the monthly total precipitation of arid regions. Azadi and Sepaskhah (2012) concluded that the ANNs did not significantly increase prediction accuracy compared with MLR. Choubin et al. (2016) compared the performance of MLR and adaptive network-based fuzzy inference system used in forecasting precipitation based on large-scale climate signals. Swain et al. (2017) developed a MLR model to reckon annual precipitation over Cuttack district, Odisha. India. Navid and Niloy (2018) employed MLRs for predicting the rainfall in Bangladesh. Study by Refona et al. (2019) applied the linear regression model for prediction of rainfall in Chennai district. Gnanasankaran and Ramaraj (2020) applied the Machine Learning (ML) algorithm and MLR model for rainfall forecasting by using a set of meteorological data including the monthly wise rainfall in India. They have found that the MLR gave better results than those values of ML. Patil et al. (2020) applied MLR, neural networks and decision trees algorithm to predict the rainfall by using the Austin weather dataset that was collected from Kaggle. Liyew and Melese (2021) made an attempt to measure the performance of three machine learning techniques (Multivariate Linear Regression, Random Forest, and Extreme Gradient Boosting (EGB)) applied in predicting the daily rainfall for Bahir Dar City, Ethiopia. The result of their study revealed that the EGB algorithm performed better than multivariate regression and random forest. Ramli et al. (2022) carried out a study on agent factors that influenced the rainfall changes at Krueng Pasee Aceh watershed, Indonesia through linear regression with a log transformation approach on predictor variables.

In view of the above, for the present study, MLR with different combination of meteorological data is applied for predication of seasonal (viz., monsoon and post-monsoon) and annual rainfall. This paper illustrates a study on prediction of seasonal daily (herein after called as seasonal) rainfall and annual daily (herein after called as annual) rainfall using three different regression models viz., Regression Model-1 (RM1) with rainfall (R), minimum temperature (Tmin) and maximum temperature (Tmax), Regression Model-2 (RM2) with R, Tmin, Tmax and average wind speed (AWS), and Regression Model-3 (RM3) with R, Tmin, Tmax, AWS and relative humidity (RH) for Mahabaleshwar and Pune regions, and the results obtained thereon.

2. METHODOLOGY

Regression is a statistical technique of data mining that has wide range of application in various fields like rainfall-runoff modelling, prediction of meteorological events, stream flow forecasting, etc. Also, regression in simple term is defined as the prediction of one variable from another variable that can be easily obtained by using simple linear regression. Thereafter, the MLR is used to describe the process by which several variables that are used to predict the desired variable. The general form of the MLR model (Liyew and Melese, 2021) is given as below:

$$Y=a_0+a_1X_1+a_2X_2+a_3X_3+.....+a_nX_n \quad (1)$$

Where, Y is the predicted value, a_i's ($i=1$ to n) are the predictor coefficients and X_i's ($i=1$ to n) are the predictors.

2.1. Model Performance Analysis

The performance of the MLR models adopted in rainfall prediction is evaluated through Model Performance Indicators (MPIs) viz., Correlation Coefficient (CC), Nash–Sutcliffe Model Efficiency (NSE) and Root Mean Squared Error (RMSE). The mathematical expressions of MPIs are given as below:

$$CC = \frac{\sum_{i=1}^{N}\left(x_i-\overline{x}\right)\left(x_i^*-\overline{x^*}\right)}{\sqrt{\left(\sum_{i=1}^{N}\left(x_i-\overline{x}\right)^2\right)\left(\sum_{i=1}^{N}\left(x_i^*-\overline{x^*}\right)^2\right)}} \quad (2)$$

$$NSE(\%)=\left(1-\frac{\sum_{i=1}^{N}\left(x_i-x_i^*\right)^2}{\sum_{i=1}^{N}\left(x_i-\overline{x}\right)^2}\right)*100$$

$$RMSE=\left(\frac{1}{N}\sum_{i=1}^{N}\left(x_i-x_i^*\right)^2\right)^{1/2}$$

Where, X_i *is the observed data of* i^{th} *sample,* X_i^* *is the predicted data of* i^{th} *sample,* $\overline{X}$ is the average of observed data and $\overline{X^*}$ is the average of predicted data (Chen and Adams, 2006). The model with high *CC*, better *NSE* and minimum *RMSE* is considered as better suited for prediction of seasonal and annual rainfall.

3. APPLICATION

This paper presents a study on prediction of seasonal (monsoon and post-monsoon) and annual daily rainfall for Pune and Mahabaleshwar regions using MLR models. Pune region lies on the western side of Deccan Plateau and is on leeward side of Sahyadri mountain range which forms a barrier from Arabian Sea. Pune region is located at approximately 18° 31′ 00″ N latitude and 73° 51′ 22" E longitude. Pune has hot semi-arid climate and receives moderate rainfall. Mahabaleshwar region is a vast plateau bounded by valley from all sides. Mahabaleshwar region is located at approximately 17° 55' 18" N latitude and 73° 39' 20″ E longitude. Mahabaleshwar receives heavy rainfall during monsoon and is cold enough in winter. The index map of the study area with locations of Pune and Mahabaleshwar are shown in Figure 1.

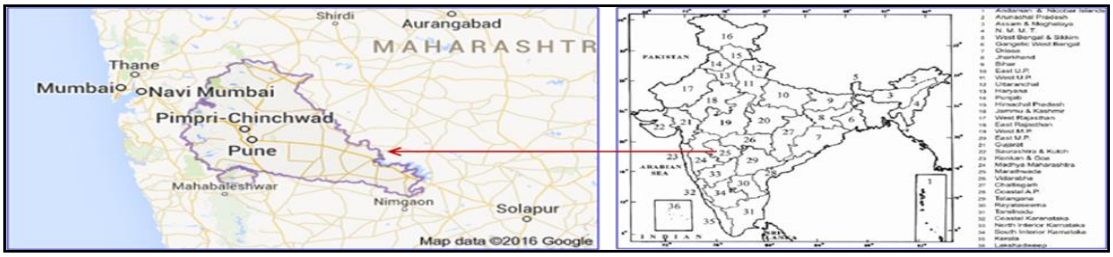


Figure 1. Index map of the study area with locations of Pune and Mahabaleshwar

In the present study, the daily series of the meteorological data viz., rainfall (R), Tmin, Tmax, AWS and RH observed at Pune and Mahabaleshwar for the period 1997 to 2019 is used. From the scrutiny of the data, it was found that the observed data for few days in a month of a year are not available and hence those values are not considered in data analysis. The seasonal (monsoon and post-monsoon) and annual series of meteorological data is extracted from the daily data and used in rainfall prediction by applying three different MLR models viz., RM1, RM2 and RM3. In the present study, 80% of the observed data is used for training and the remaining 20% is used for testing.

As the units of the meteorological data viz., R (in mm), Tmax and Tmin (in ^oC), AWS (in km/hour) and RH (in percentage) considered in the study are of different units, these values are normalized through Eq. (3) and also used in rainfall prediction. After completion of training and testing process, the output data is again denormalized through Eq. (3) to achieve the results in original domain.

$$Nor(X_i) = \frac{X_i - Min(X_i)}{Max(X_i) - Min(X_i)} \quad (3)$$

Where, $Nor(X_i)$ is the normalized value of X_i, $Min(X_i)$ is the series minimum value of X_i and $Max(X_i)$ is the series maximum value of X_i.

4. RESULTS AND DISCUSSION

By applying the procedures of MLR models, as described above, prediction of seasonal and annual rainfall for Pune and Mahabaleshwar was carried out. In this paper, SPSS (Statistical Package for the Social Sciences) was used to develop the MLRs with different combination of meteorological data considered in the study.

4.1. Prediction of Seasonal and Annual Rainfall using MLR

In the present study, the normalized values of meteorological data were used to develop a MLR models (Table 1) for prediction of seasonal rainfall for Pune and Mahabaleshwar. By using the developed MLR models (viz., RM1, RM2 and RM3), the normalized values of rainfall were estimated and thereafter denormalized through Eq. (3) to get the predicted rainfall in original domain. The

descriptive statistics of the observed and predicted values of seasonal and annual rainfall using RM1, RM2 and RM3 for Pune and Mahabaleshwar are given in Tables 2 to 4. The time series plots of predicted rainfall using RM1, RM2 and RM3 with observed rainfall for monsoon, post-monsoon and annual periods of Pune and Mahabaleshwar are presented in Figures 2 to 4 respectively.

Table 1. MLR models used in prediction of seasonal rainfall for Pune and Mahabaleshwar

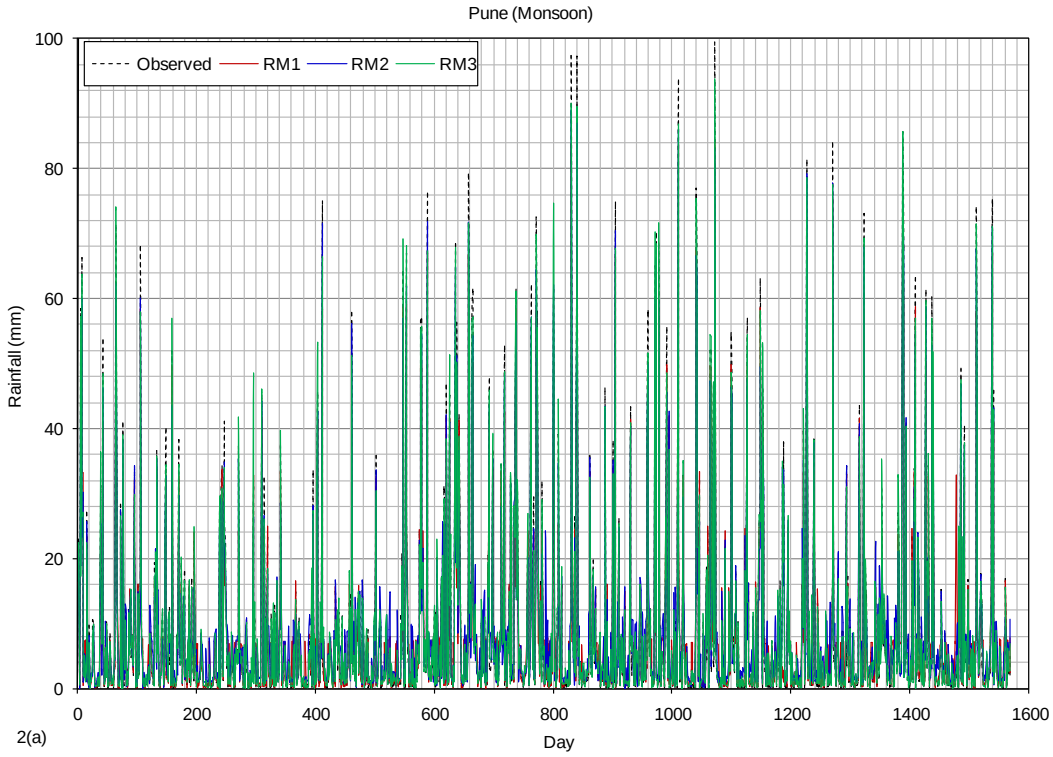
Region	MLRs using normalized values of predictors		
	RM1	RM2	RM3
Pune			
Monsoon	NR(t+1) = 2.678 NR(t) - 0.221 NTmin + 1.395 NTmax - 0.972	NR(t+1) = 2.835 NR(t) - 0.234 NTmin + 1.478 NTmax - 2.013 NAWS + 1.029	NR(t+1) = 2.993 NR(t) - 0.247 NTmin + 1.559 NTmax - 2.125 NAWS + 0.824 RH - 1.086
Post-monsoon	NR(t+1) = 1.297 NR(t) - 0.296 NTmin + 0.714 NTmax - 0.591	NR(t+1) = 1.373 NR(t) - 0.313 NTmin + 0.756 NTmax - 1.626 NAWS + 0.626	NR(t+1) = 1.450 NR(t) - 0.331 NTmin + 0.798 NTmax - 1.717 NAWS + 0.776 RH - 0.660
Annual	NR(t+1) = 2.835 NR(t) - 0.234 NTmin + 1.477 NTmax - 1.283	NR(t+1) = 2.993 NR(t) - 0.247 NTmin + 1.559 NTmax - 2.125 NAWS + 1.354	NR(t+1) = 3.150 NR(t) - 0.260 NTmin + 1.641 NTmax - 2.237 NAWS + 0.867 RH - 1.425
Mahabaleshwar			
Monsoon	NR(t+1) = 1.334 NR(t) - 0.206 NTmin + 0.279 NTmax - 0.098	NR(t+1) = 1.412 NR(t) - 0.218 NTmin + 0.295 NTmax - 0.116 NAWS + 0.104	NR(t+1) = 1.491 NR(t) - 0.230 NTmin + 0.312 NTmax - 0.123 NAWS + 0.714 RH - 0.109
Post-monsoon	NR(t+1) = 0.553 NR(t) - 0.069 NTmin + 0.106 NTmax - 0.064	NR(t+1) = 0.585 NR(t) - 0.073 NTmin + 0.113 NTmax - 0.017 NAWS + 0.068	NR(t+1) = 0.618 NR(t) - 0.077 NTmin + 0.119 NTmax - 0.018 NAWS + 0.243 RH - 0.071
Annual	NR(t+1) = 1.412 NR(t) - 0.218 NTmin + 0.295 NTmax - 0.104	NR(t+1) = 1.491 NR(t) - 0.230 NTmin + 0.312 NTmax - 0.123 NAWS + 0.109	NR(t+1) = 1.569 NR(t) - 0.242 NTmin + 0.328 NTmax - 0.129 NAWS + 0.752 RH - 0.115
NR(t)	:	Normalized value of rainfall of t^{th} day	
NR(t+1)	:	Normalized value of rainfall of $t+1^{th}$ day	
NTmax	:	Normalized value of maximum temperature	
NTmin	:	Normalized value of minimum temperature	
NAWS	:	Normalized value of average wind speed	
NRH	:	Normalized value of relative humidity	

Table 2. Descriptive statistics of observed and predicted seasonal rainfall using RM1, RM2 and RM3 for Pune

Descriptive statistics	Observed rainfall		Predicted rainfall					
			RM1		RM2		RM3	
	Training	Testing	Training	Testing	Training	Testing	Training	Testing
Monsoon								
Average (mm)	8.5	8.0	7.9	8.2	8.7	8.8	8.6	8.1
SD (mm)	14.5	14.1	12.2	12.0	12.7	12.5	13.9	13.5
CS	2.998	3.253	2.942	3.169	3.032	3.316	2.959	3.165
CK	10.054	11.463	9.827	11.395	10.535	12.047	9.669	10.897
Post-monsoon								
Average (mm)	10.0	12.2	9.2	11.8	11.3	12.8	10.5	12.5
SD (mm)	13.9	18.1	11.5	15.8	13.1	16.9	14.6	18.3
CS	2.671	2.789	2.696	3.246	2.613	2.832	2.248	2.645
CK	9.819	9.951	9.547	13.688	9.725	10.139	6.254	8.283
SD: Standard Deviation; CS: Coefficient of Skewness; CK: Coefficient of Kurtosis								

By using the descriptive statistics, as given in Table 2, the percentage of variation in average of predicted rainfall using RM1, RM2 and RM3 with reference to the average of observed rainfall during testing period was computed as 2.5%, 10.0% and 1.3% respectively for monsoon season of Pune. Likewise, for post-monsoon season of Pune, these values were computed as 3.3%, 4.9% and 2.5% respectively. From Table 3, it was observed that the percentage of variation in average of predicted rainfall using RM1, RM2 and RM3 with reference to the average of observed rainfall during testing period is 6.8%, 6.0% and 1.5% respectively for monsoon season of Mahabaleshwar. Also, for post-monsoon of Mahabaleshwar, these values were computed as 22.4%, 28.4% and 20.9% respectively.

From Figures 2 and 3, it can be seen that the predicted rainfall using RM3 is closer to the observed rainfall for monsoon and post-monsoon seasons of Pune and Mahabaleshwar.



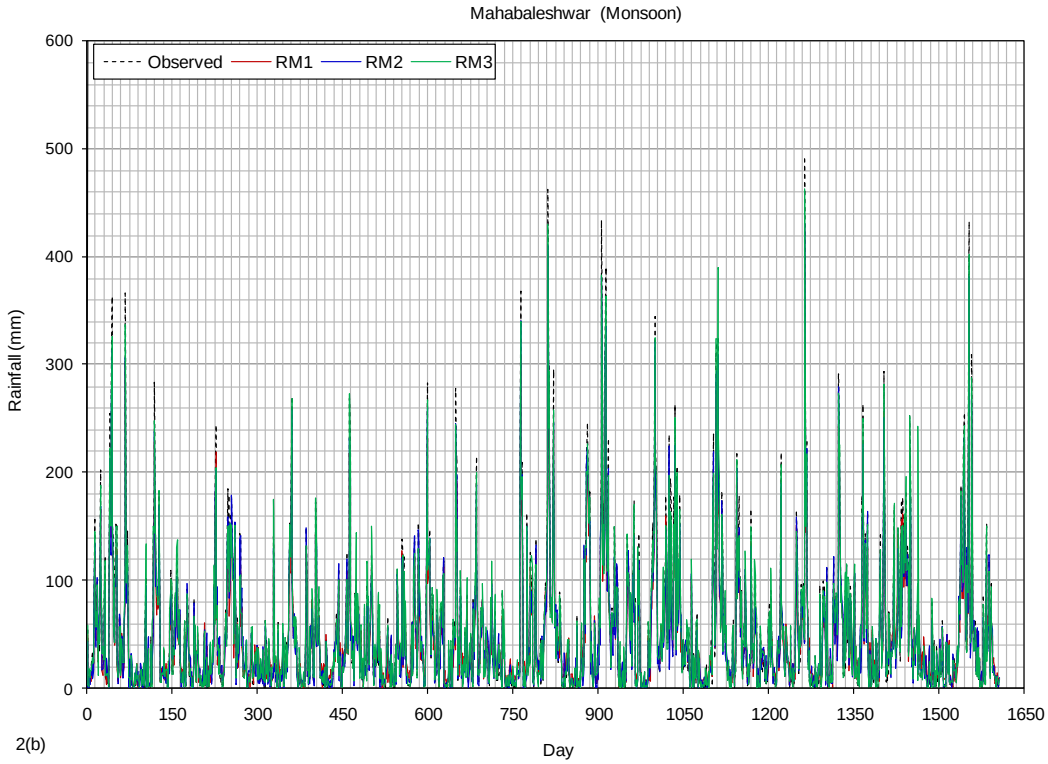
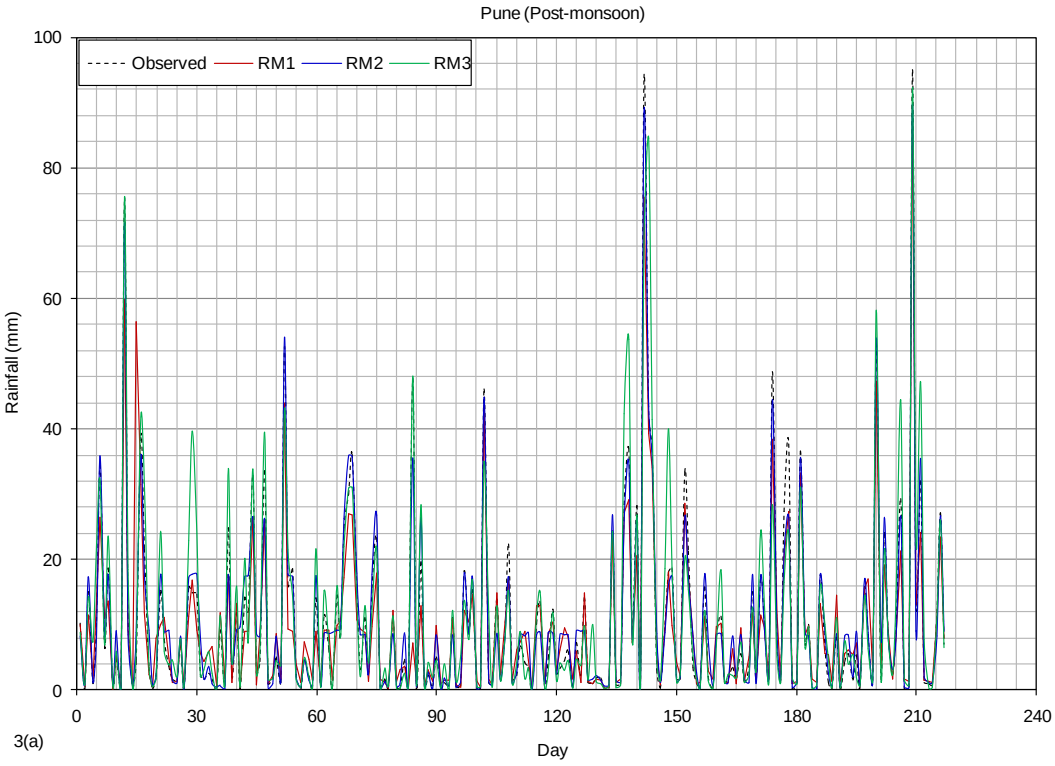
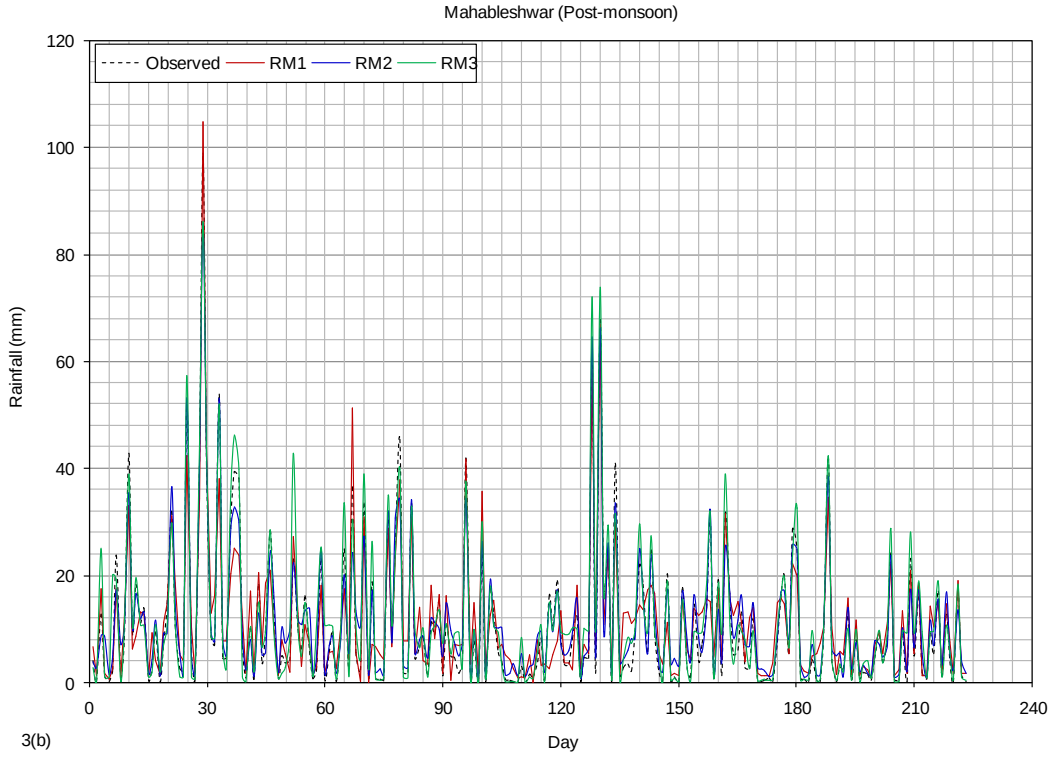


Figure 2. Plots of predicted rainfall using RM1, RM2 and RM3 with observed rainfall for monsoon season of Pune and Mahabaleshwar

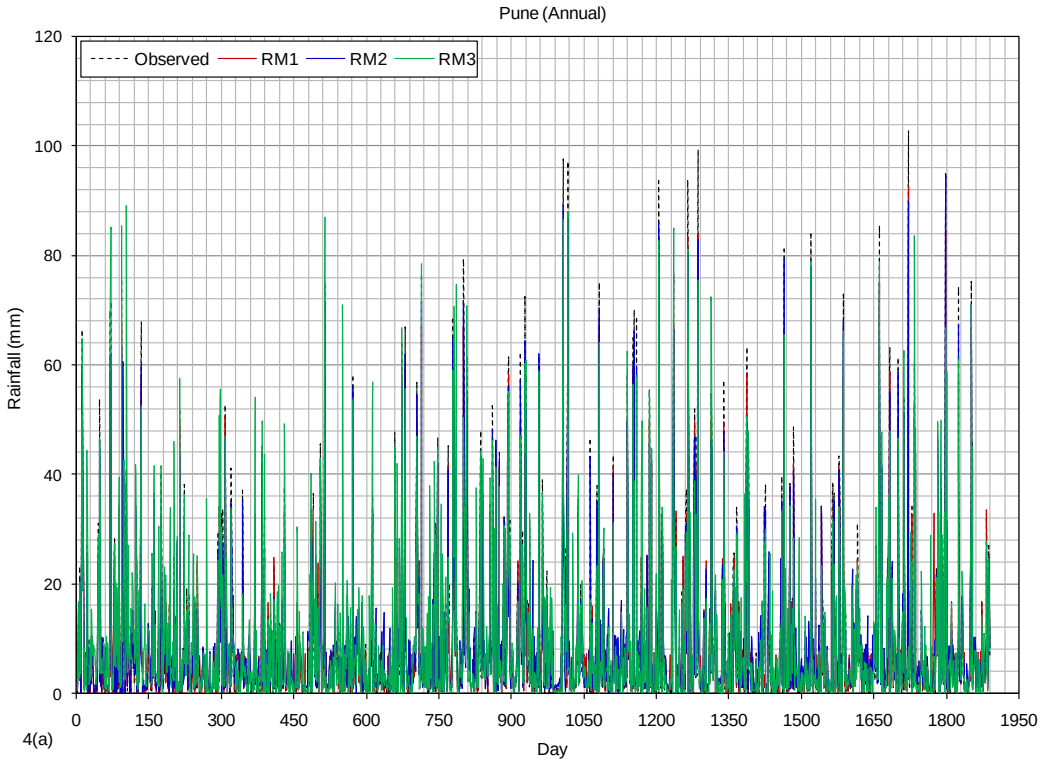


3(a)



3(b)

Figure 3. Plots of predicted rainfall using RM1, RM2 and RM3 with observed rainfall for post-monsoon season of Pune and Mahabaleshwar



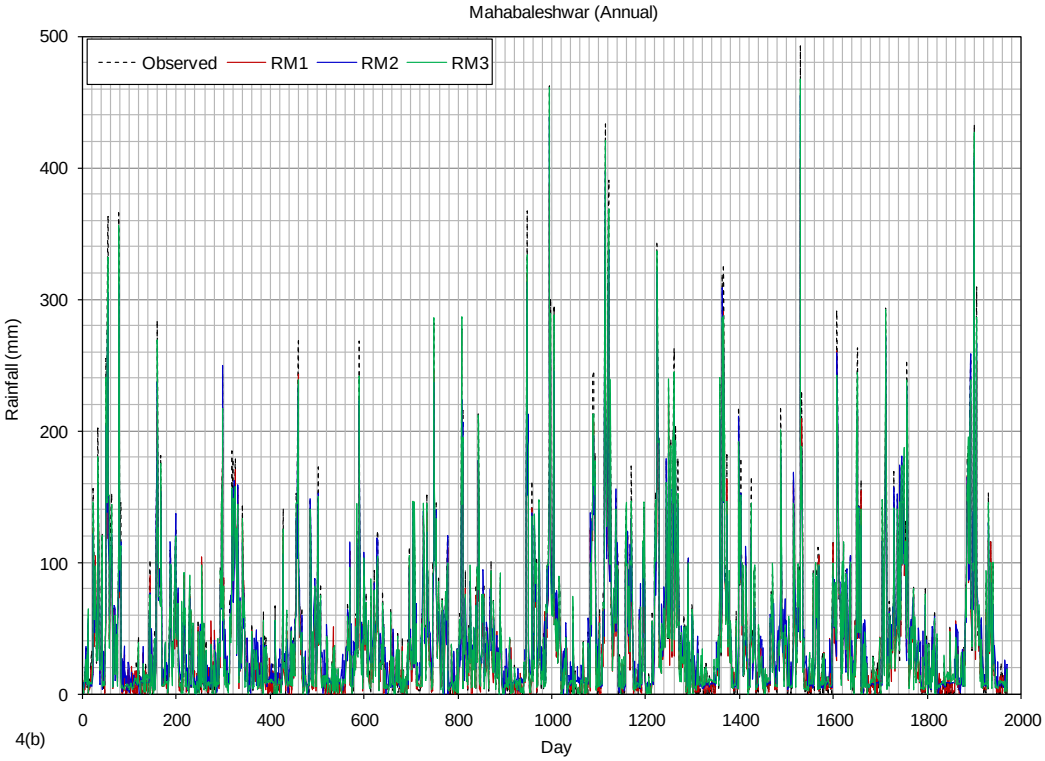


Figure 4. Plots of predicted annual rainfall using RM1, RM2 and RM3 with observed rainfall for Pune and Mahabaleshwar

Table 3. Descriptive statistics of observed and predicted seasonal rainfall using RM1, RM2 and RM3 for Mahabaleshwar

Descriptive statistics	Observed rainfall		Predicted rainfall					
			RM1		RM2		RM3	
	Training	Testing	Training	Testing	Training	Testing	Training	Testing
Monsoon								
Average (mm)	50.7	54.6	46.0	50.9	47.1	51.3	51.6	55.4
SD (mm)	62.9	62.3	51.6	50.5	55.8	53.1	58.9	60.2
CS	2.460	2.099	2.612	2.289	2.468	2.145	2.393	1.985
CK	8.228	6.065	9.576	7.672	8.203	6.458	8.106	5.188
Post-monsoon								
Average (mm)	11.5	6.7	13.2	8.2	13.0	8.6	12.7	8.1
SD (mm)	14.7	8.8	13.3	7.6	13.0	7.8	14.8	9.7
CS	2.384	2.112	3.034	1.355	2.496	2.015	2.493	1.828
CK	8.008	5.273	14.593	2.011	8.187	4.963	8.926	3.404

Table 4. Descriptive statistics of observed and predicted annual rainfall using RM1, RM2 and RM3 for Pune and Mahabaleshwar

Descriptive statistics	Observed rainfall		Predicted rainfall					
			RM1		RM2		RM3	
	Training	Testing	Training	Testing	Training	Testing	Training	Testing
Pune								
Average (mm)	8.5	8.6	8.1	8.9	8.7	9.3	9.7	8.7
SD (mm)	14.1	15.3	12.1	13.2	12.5	13.6	14.0	13.9
CS	2.988	3.298	2.908	3.295	3.012	3.415	2.643	2.912
CK	10.310	12.348	9.959	12.862	10.670	13.484	8.147	9.283
Mahabaleshwar								
Average (mm)	43.7	44.2	38.6	39.7	44.7	45.7	41.7	44.9
SD (mm)	59.2	59.2	49.7	48.4	50.9	51.5	55.8	55.9
CS	2.692	2.399	2.681	2.409	2.805	2.510	2.751	2.464
CK	9.892	7.622	9.741	7.968	11.410	9.271	10.478	8.278

By using the values of descriptive statistics, as given in Table 4, the percentage of variation in average of predicted rainfall using RM1, RM2 and RM3 with reference to the average of observed rainfall during testing period was computed as 3.5%, 8.1% and 1.2% respectively for Pune. Likewise, for Mahabaleshwar, these values were computed as 10.2%, 3.4% and 1.6% respectively for Mahabaleshwar. From Figure 4, it can be seen that the predicted annual rainfall using RM3 is closer to the observed annual rainfall for Pune and Mahabaleshwar.

4.2. Analysis of Results Based on MPIs

The performance of RM1, RM2 and RM3 applied in prediction of seasonal daily and annual daily rainfall for Pune and Mahabaleshwar was evaluated by using MPIs and the results are presented in Tables 5 and 6. Based on MPIs values, the findings drawn from the study were summarized and are given as below:

i) The RMSE on the predicted seasonal and annual rainfall using RM3 was found as minimum when compared with those values of RM1 and RM2 for Pune and Mahabaleshwar.

ii) From the CC values, it was noted that there is generally good correlation between the observed and predicted values using RM1, RM2 and RM3 for seasonal and annual rainfall. The CC values in the rainfall prediction using RM1, RM2 and RM3 varied from 0.906 to 0.973 for Pune while 0.963 to 0.987 for Mahabaleshwar.

iii) For monsoon and post-monsoon seasons of Pune, the NSE given by RM3 in testing period was computed as 98.6% and 97.4% respectively. For Mahabaleshwar, the NSE given by RM3 was computed as 96.3% for monsoon season while 96.7% for post-monsoon.

iv) For annual rainfall, the NSE given by RM3 during testing period was computed as 94.6% for Pune and 98.2% for Mahabaleshwar.

v) Based on the analysis of the results using MPIs, it was identified that the RM3 is better suited amongst three models (viz., RM1, RM2 and RM3) applied in predicting the seasonal and annual rainfall for Pune and Mahabaleshwar.

Table 5. MPIs values given by RM1, RM2 and RM3 for seasonal and annual rainfall of Pune

MPIs	RM1		RM2		RM3	
	Training	Testing	Training	Testing	Training	Testing
Monsoon						
CC	0.969	0.967	0.971	0.972	0.970	0.973
NSE (%)	93.0	92.4	94.5	93.7	97.9	98.6
RMSE (mm)	3.817	3.887	3.397	3.530	2.085	1.658
Post-monsoon						
CC	0.906	0.972	0.912	0.962	0.970	0.968
NSE (%)	79.4	95.6	80.8	92.1	94.9	97.4
RMSE (mm)	6.332	3.749	6.115	5.011	3.126	2.863
Annual						
CC	0.973	0.971	0.912	0.906	0.967	0.972
NSE (%)	93.2	93.5	80.6	80.9	93.8	94.6
RMSE (mm)	3.699	3.815	6.220	6.674	3.794	3.556

Table 6. MPIs values given by RM1, RM2 and RM3 for seasonal and annual rainfall of Mahabaleshwar

MPIs	RM1		RM2		RM3	
	Training	Testing	Training	Testing	Training	Testing
Monsoon						
CC	0.987	0.985	0.985	0.986	0.987	0.973
NSE (%)	94.5	90.2	96.2	94.7	97.2	96.3
RMSE (mm)	14.683	15.770	12.206	12.367	10.593	10.391
Post-monsoon						
CC	0.963	0.965	0.974	0.978	0.963	0.967
NSE (%)	86.4	88.7	93.9	93.7	96.3	96.7
RMSE (mm)	5.418	2.982	4.175	2.856	3.628	2.214
Annual						
CC	0.984	0.987	0.982	0.980	0.982	0.987
NSE (%)	94.3	94.0	93.3	93.0	98.0	98.2
RMSE (mm)	14.179	14.499	15.378	15.616	7.930	7.850

5. CONCLUSIONS

The paper presented a study on prediction of seasonal and annual rainfall using MLR models (viz., RM1, RM2 and RM3) for Pune and Mahabaleshwar. The performance of the models applied in rainfall prediction was evaluated by using MPIs viz., CC, NSE and RMSE. On the basis of the evaluation of the results through MPIs, some of the conclusions drawn from the study were summarized and are presented below:

- The time series plots showed that the predicted seasonal and annual rainfall by RM3 is comparative better than those values of RM1 and RM2.
- The CC values indicated that there was generally a good correlation between the observed and predicted rainfall using RM1, RM2 and RM3, and these values vary from 0.906 to 0.973 for Pune while 0.963 to 0.987 for Mahabaleshwar.
- During testing period, the NSE for prediction of monsoon rainfall using RM3 was computed as 98.6% for Pune while 96.3% for Mahabaleshwar. For post-monsoon season, these values were computed as about 97%.

- The NSE in predicting the annual rainfall using RM3 for Pune and Mahabaleshwar during testing period was computed as 94.6% and 98.2%.
- For monsoon and post-monsoon seasons of Pune, the percentage of variation in average of predicted rainfall using RM3 with reference to the average of observed rainfall was computed as 1.3% and 2.5% in testing period. For Mahabaleshwar, these values were computed as 1.5% for monsoon season and 20.9% for post-monsoon season.
- The percentage of variation in the average of predicted annual rainfall using RM3 with reference to the average of observed rainfall during testing period was computed as 1.2% for Pune and 1.6% for Mahabaleshwar.

In light of the above, the study suggested that the predicted seasonal and annual daily rainfall using RM3 with all meteorological data (viz., Rainfall, Tmax, Tmin, AWS and RH) could be used for design purposes. The outcomes of the study would also be useful for stakeholders for planning, design and management of water resources projects in Pune and Mahabaleshwar regions.

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