Journal of Modeling and Optimization 2020;12(1):60-69
https://doi.org/10.32732/jmo.2020.12.1.60

Forecasting of Summer Monsoon Rainfall over Gangetic West Bengal, India Utilising Intrinsic Mode Functions, Linear and Neural Regression

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Received: 25 March 2020; Accepted: 1 May 2020; Available online: 10 June 2020

Abstract: The South West Monsoon rainfall data of the meteorological subdivision number 6 of India enclosing Gangetic West Bengal is shown to be decomposable into eight empirical time series, namely Intrinsic Mode Functions. This leads one to identify the first empirical mode as a nonlinear part and the remaining modes as the linear part of the data. The nonlinear part is modeled with the technique Neural Network based Generalized Regression Neural Network model technique whereas the linear part is sensibly modeled through simple regression method. The different Intrinsic modes as verified are well connected with relevant atmospheric features, namely, El Nino, Quasi-biennial Oscillation, Sunspot cycle and others. It is observed that the proposed model explains around 75% of inter annual variability (IAV) of the rainfall series of Gangetic West Bengal. The model is efficient in statistical forecasting of South West Monsoon rainfall in the region as verified from independent part of the real data. The statistical forecasts of SWM rainfall for GWB for the years 2012 and 2013 are108.71 cm and 126.21 cm respectively, where as corresponding to the actual rainfall of 93.19 cm 115.20 cm respectively which are within one standard deviation of mean rainfall.
Keywords: South West Monsoon (SWM) rainfall; Intrinsic Mode Function (IMF); Generalized Regression Neural Network (GRNN); Quasi-biennial Oscillation (QBO); Inter annual variability (IAV).

1. Introduction

The summer monsoon or so called the South West Monsoon (SWM) rainfall comprising of the rainfalls of the months of June, July, August and September, is the substantial component of annual rainfall in India as well as the meteorological sub division number 6 covering the region of Gangetic West Bengal (GWB). The economy and agriculture are vastly dependent on the characteristics of SWM rainfall. The time series for different spatial and time scales are the primary concern of scientists [1], [2], [3]. Figure 1 shows the meteorological sub divisions of India including GWB.

In fact, efforts are made from earlier times to understand the connections between SWM rainfall and other global and atmospheric phenomenon. As an example, [4] links between the Indian monsoonal rainfall data and the global Sea Surface Temperature (SST) data. The other approach leads to, simply modeling the past data a year ahead with an insignificant error band to achieve forecast without linking with the phenomenon.

There are some studies that elaborate the periods latent in the data with the help of Fourier decomposition, namely, Quasi-biennial Oscillation (QBO) [5], tidal forcing [6], El-Nino Southern Oscillation (ENSO) [7], [8], Sunspot Cycle [9] and intra-seasonal periodicities [10], [7].

The conventional method of analysis of rainfall data counts on stationary random process with Gaussian property [11], [3]. For SWM rainfall series of GWB, the investigations on auto-correlation and power-spectral density indicates that those are too weak for modeling as linear time series [12]. However, the particular form of the nonlinear model to be used is, perhaps, not known.

On the other hand, the decomposition of SWM rainfall upon application of principal components and understanding the nature of the components are very useful study for identifying coherent zones and nature of the components [11], [12], [13].

The rainfall time series is supposed to carry the causes in itself. With this connection the works of [14], [15] may be referred where though causes are not known, with sufficient data series rainfall is suitably empirically modeled.

In the last decade, it has been pointed out that nonlinear model with variable frequency harmonic terms can be effectively used to explain majority of the inter annual variation (IAV) and indicated that the rainfall data can be decomposed into hierarchical Integral Mode Functions (IMFs) as signals if the basic data is not a white noise [16].

The approach has been examined at all India level by Iyenger and Raghukant [15]. Recently, a few literatures are available of this approach in other countries like Australia and Caspian catchment area [19], [20] respectively.

However, the variability study and forecasting exercise has received little attention in the region of GWB (meteorological subdivision No. 6) in the southern plain of the state West Bengal, India. The importance of the region is very much known for its primary role in industry, agriculture and civilization. In the present paper, a new representation of the SWM rainfall of GWB in terms of narrow band IMF series is studied. These time series are simpler than the original data for modeling and forecasting.

The structure of the paper is as follows. Firstly, the Empirical Modes called IMFs of GWB would be discussed. Thereafter, forecasting strategy would be presented. A combination of Multiple Linear Regression analysis and Generalized Regression Neural Network (GRNN) architecture would be discussed. Lastly, an analysis on the performance of model would be provided.

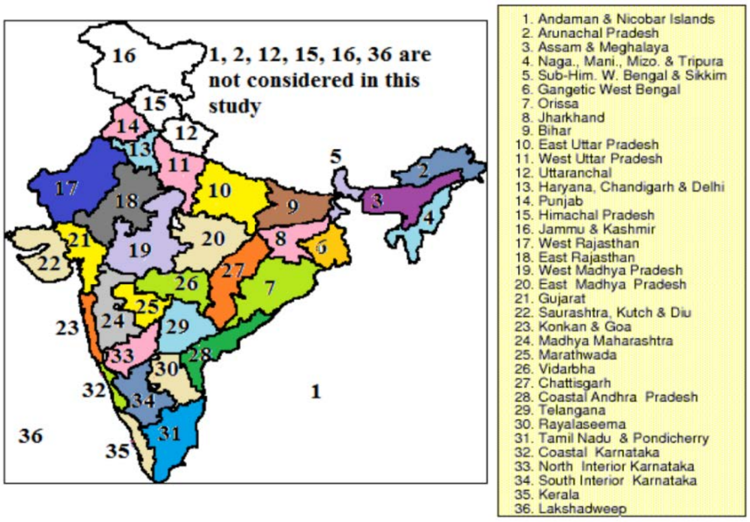

Figure 1. Meteorological Subdivisions including Gangetic West Bengal (GWB)

2. Rainfall data

The rainfall data of GWB are collected from the website www.tropmet.res.in of Indian Institute of Tropical Meteorology (IITM), Pune. The SWM rainfall data for the period 1871-2013 which is the sum of the monthly rainfall values of June, July, August and September are selected for detailed study. The SWM data of GWB are presented in Figure 2 for preliminary idea. Some basic statistics of the data such as the *Climatic Normal* (m_R) and *Climatic Deviation* about the Normal (σ_R) are presented in Table 1.

Table 1. SWM rainfall data (1871-2001)

Region	Area (Sq. Km.)	Mean (cm)(m_R)	Std. dev. (σ_R)	Skewness	Kurtosis
GWB	44300	106.93	10.2734	-0.4425	2.9845

* GWB: Gangetic West Bengal

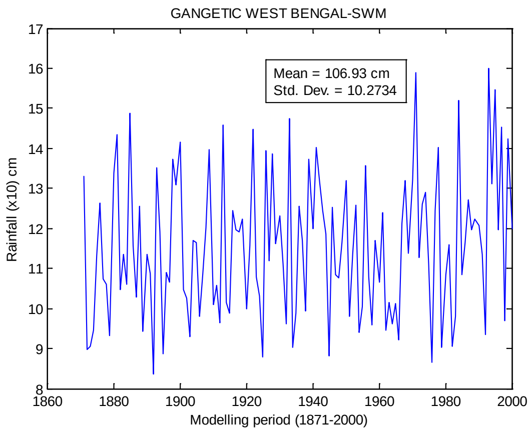

Figure 2. SWM rainfall of GWB for modeling period (1871-2000)

3. Intrinsic Mode Functions (IMFs)

The time series of the SWM rainfall is decomposed into number of empirical modes, in other words, Intrinsic Mode Functions (IMFs) series. These IMF series identify dominant period and amplitudes as indicated by Huang *et al.* [17]. As mentioned in their work, these series are uncorrelated with each other at zero lag but correlated with SWM data in decreasing order of importance.

A total of eight IMF series, namely, IMF_1, $IMF_{2,...,}$ IMF_8 are *hierarchically* extracted till the sieved data indicates no sign of oscillations. Each IMF is a narrow band process and possesses identifiable central periods. Long-term climate trends along with centre-line drifts, specific frequency or period and long period non-stationary features emerges as the eight IMFs. For the time series of Figures 3-10, eight IMFs of SWM rainfall are presented. It is observed that the last two IMFs i.e. IMF_7 and IMF_8 are invariably positive and is a slowly varying mode around the long-term average [17]. The process may be thought of as the normal or climatic component about the IAV of the appearing monsoon rainfall occurs. The sum of all the IMF series at a particular time is equal to the original SWM data series to the higher level of accuracy.

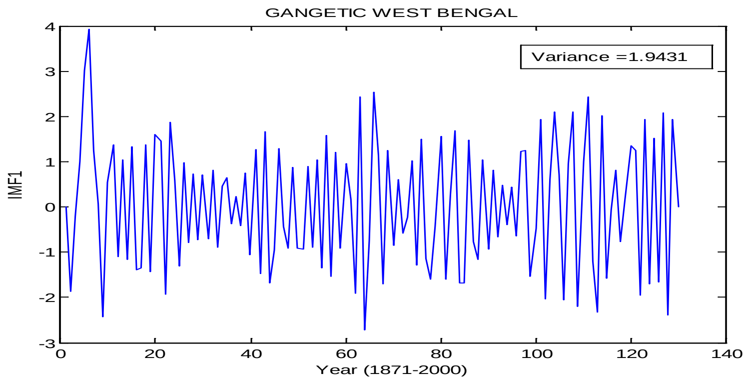

Figure 3. First Intrinsic Mode Function (IMF_1) of SWM rainfall of GWB

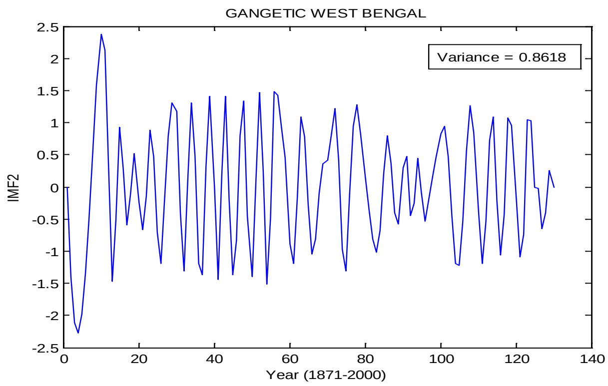

Figure 4. Second Intrinsic Mode Function (IMF_2) of SWM rainfall of GWB

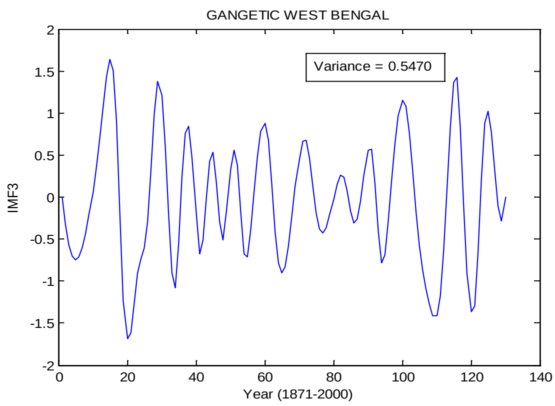

Figure 5. Third Intrinsic Mode Function (IMF_3) of SWM rainfall of GWB

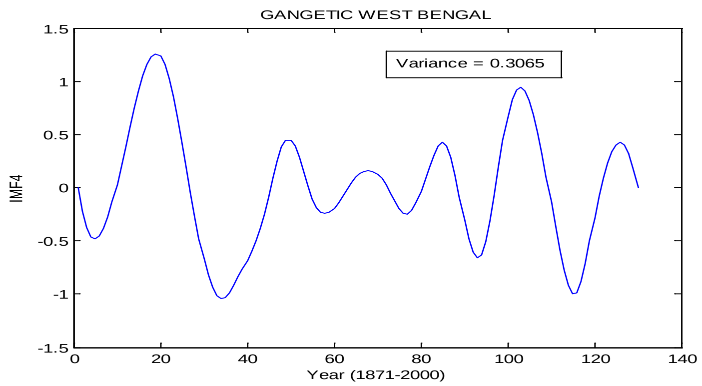

Figure 6. Fourth Intrinsic Mode Function (IMF_4) of SWM rainfall of GWB

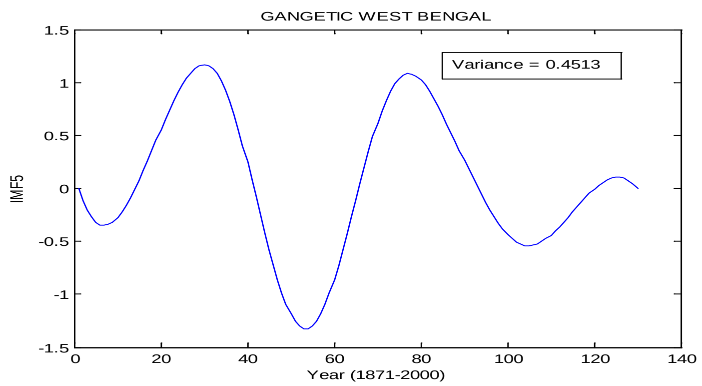

Figure 7. Fifth Intrinsic Mode Function (IMF_5) of SWM rainfall of GWB

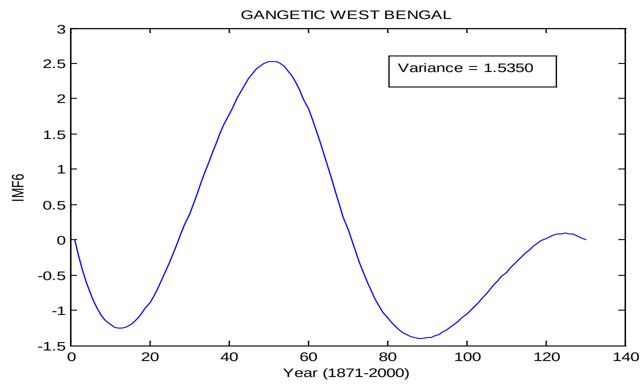

Figure 8. Sixth Intrinsic Mode Function (IMF_6) of SWM rainfall of GWB

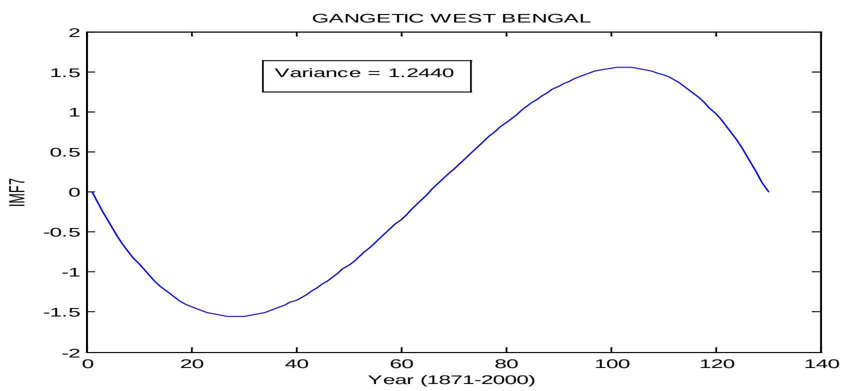

Figure 9. Seventh Intrinsic Mode Function (IMF_7) of SWM rainfall of GWB

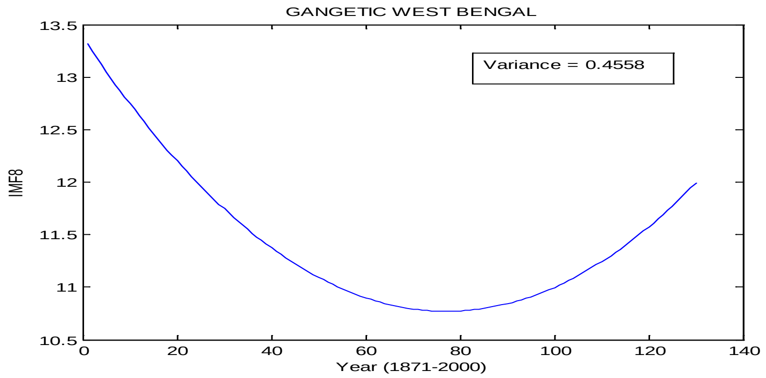

Figure10. Eighth Intrinsic Mode Function (IMF_8) of SWM rainfall of GWB

Table 2. Central period (T) of the IMF's in years and % variance contributed to IAV

Region	IMF1		IMF2		IMF3		IMF4		IMF5		IMF6		IMF7		IMF8	
	T	IAV%	T	IAV%	T	IAV%	T	IAV%	T	IAV%	T	IAV%	T	IAV%	T	IAV%
GWB	2.71	62.82	5.91	28.07	13.00	17.69	21.66	4.17	43.33	14.59	65	4.94	>100	16.94|	Not detectable	6.20

*GWB: Gangetic West Bengal

The contribution of the IMF series are computed found on the basis of time averaging and project the relative contribution of an IMF to the total variability of the rainfall. It is observed that all IMFs exhibit slowly varying amplitudes and frequencies (Figures 3-10) indicating a narrow band process. The dominant period of oscillation can be found by counting the zeros and the extrema in an IMF series. In Table 2, the central period and the contribution of each IMF to IAV percentage is listed. It is observed that IMF_1 is a predominant mode with an average period of 2.71 years contributing to 62.82% of IAV. IMF_2 is the second most important mode with a dominant period of 5.91years contributing to 28.07% of IAV. These two modes are closely connected with the Quasi-biennial Oscillation (QBO) and El Niño–Southern Oscillation (ENSO) phenomenon respectively as evidenced in case of All India level [16]. In the same way, IMF_3 with time period of about 13 years contributing to 17.69% of IAV can be associated with the sunspot cycle of about 11 years period which is in agreement with the works of Bhalme and Jadav [9].

The central period of IMF_4 is about 21 years which is closely connected to tidal forcing of about 19 years of quasi-cycle of Indian monsoon in agreement with the works of Campbell *et al.* [6]. The IMF_5 shows an elongated period of 43 years may follow [17].

This way, IMF_6 is here identified as frequently connected to the elongated mode of 65 years contributing about 5% of IAV represents the presence of six quasi–cycle modes as indicated by Narashima and Kailash [7] using wavelet analysis of Indian monsoon rainfall. The IMF_7 and IMF_8 contributing about period of 100 years and above are the presence of fragmented slowly varying long-term deterministic shift of monsoon in the GWB about which SWM rainfall is changing. This part is undetected in Indian monsoon rainfall of India [15]

4. IMF statistics

For understanding the statistical relation between the IMFs and the data, one has to construct the correlation matrix of the time series. In Table 3, the correlation matrix (7x7) of the SWM GWB data and the seven variable IMFs are shown. It is understood that the correlation values between the data and few IMFs, namely IMF_1, IMF_2 and IMF_3 are statistically significant and are phenomenally meaningful. Also, the IMFs are themselves uncorrelated, expecting sum of the variances of the IMFs to be closely equal to total variance of the data; small effect of sample size being neglected. This enables us to identify inherent Intrinsic Modes that constitute the overall behavior of the data.

5. Forecasting strategy

Forecasting may be understood as extending the data series stepwise for the future years. In this context, Modeling is a equation that closely matches the data with a minimum error. For simple functions with an analytic form, the exercise can be easily carried out by Talyor's series expansion; as the rainfall data is highly erratic, no simple linear function can be fitted to the data series. The decomposition of data into IMF series seems to be an alternative approach for forecasting monsoonal rainfall of a region using the decomposed IMF series, which is certainly simpler than the original data.

SWM rainfall, as a random variable is Gaussian except a few stations [3], [12], [16], so far data studied here. The possibility of forecasting of SWM rainfall incorporating IAV is now switched over to the eight hierarchical IMFs. The first IMF carries the higher frequency end of the information and is expected to be higher and more random than the others. A new feature of bi-modality emerges for the first IMF and is easily understood from the histogram (Figure 11) that negates the possibility of Gaussianness. The exhibited behavior of bi-modality indicates strong non-linearity in the dynamics of the process and rules out existence of linear auto-regressive representation. It is supported by the Chi-square test with constructed 14 intervals. The test reveals that IMF_1 is non-Gaussian at 5% level with observed values of Chi-square as 25.67 at 13 degrees of freedom.

Table 3. Correlation matrix of IMFs of GWB

	Data	IMF_1	IMF_2	IMF_3	IMF_4	IMF_5	IMF_6	IMF_7
Data	1.0000	0.6728*	0.4665*	0.3578*	0.1159	-0.0411	0.0465	0.0426
IMF_1		1.0000	-0.1059	-0.1243	-0.0125	-0.0284	-0.0445	-0.0035
IMF_2			1.0000	0.1337	0.0271	0.0057	0.0143	+0.0134
IMF_3				1.0000	-0.0297	0.0080	0.0081	-0.0286
IMF_4					1.0000	-0.0032	-0.2570	-0.0031
IMF_5						1.0000	-0.4380*	-0.1249
IMF_6							1.0000	-0.4817
IMF_7								1.0000

*Significant at 5% level.

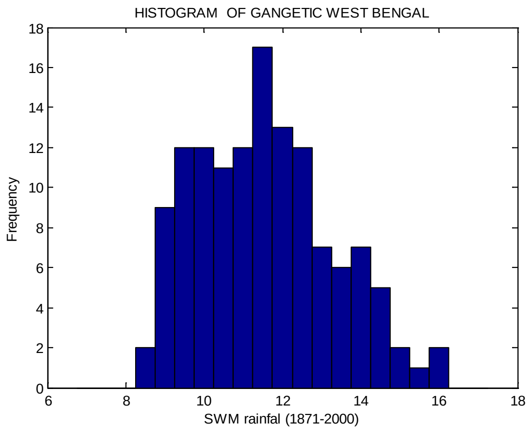

Figure 11. Histogram of IMF_1 showing bi-modality.

However, IMF_1 is stationary as examined by the standard run test of decadal variance about the median (which counts to 7 and within the range 4-11 with 13 decades at 5% level). This part of IMF_1 is considered as non-linear part. Excluding the first IMF, the remaining part ($R_j – IMF_1$) of the series is tested for Gaussianness and stationarity as detailed. The Gaussianness has been revealed by Chi-square test and the stationarity of this part been verified by the standard run test on decadal variance.

The remaining other part ($R_j – IMF_1$) is now considered as linear part and can be modeled through multiple linear regressions from own past values. The representation for the linear part y_n is chosen as

$$y_{n+1} = C_1R_n + C_2y_{n-1} + C_3y_{n-2} + C_4y_{n-3} + C_5y_{n-4} + C_6 \quad (1)$$

It is found that the equation (1) provides an excellent fit for the linear part with the data base.

Table 4. Regression coefficients of Equation (1)

Region	C_1	C_2	C_3	C_4	C_5	C_6	$Ϭ_y(e)$	Correlation Coefficient (CC)
GWB	0.1196	1.5425	-1.6454	1.1161	0.4727	3.9072	0.5394	0.9144

* GWB: Gangetic West Bengal

The regression coefficients are found from the data series of 1871–2000, leaving first 4 years as regression equation contains upto y_{j-4} terms by least square method and the resulting standard deviation of the error $Ϭ_y(e)$ and correlation coefficient (CC) between actual data and the model fitted are presented in Table 4. The correlation is highly significant endorsing the appropriateness of identifying y_j as the linear part of SWM rainfall of GWB.

6. Generalized Regression Networks architecture connected to non linear IMF_1

The first IMF that accounts for most of IAV of monsoon rainfall is non-Gaussian and non-linear process. In the case unstructured complex problem, the Generalized Regression Neural Network (GRNN) an improved version of Neural Network class of technology based on non-parametric regression, suggested by Specht [18] is applied.

6.1. Architecture of GRNN

A GRNN model contains two hidden layers, pattern neurons and summation neurons. The calculations performed in each pattern neuron of GRNN are exp $(-D_j^2/2\sigma^2)$, D_j being the distance between training sample and σ being smoothness parameter, the normal distribution is considered at each training sample. The signals of the pattern neuron, going into the Denominator neuron are weighted with corresponding values of the training samples Y_j. The weights on the signals going into the Numerator are one. Each sample from the training data influences every point that is being predicted by GRNN.

The author [18] showed that GRNN works for modeling and extending regression, prediction, classification and function approximation. The idea is that every training sample will represent mean to a radial basis neuron. After several trials with number of previous values of IMF_1, a GRNN with hidden layer is utilized as shown in Figure 12.

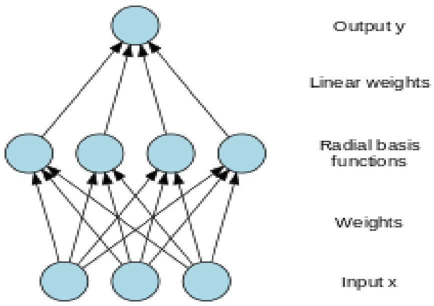

Figure 12. General Regression Neural Network with Radial Basis Functions

6.2. Results of IMF_1 with GRNN

The computation has been done using MATLAB toolbox on GRNN algorithms, with 1871-2000 as the training period. With the help of antecedent IMF_1 values, the GRNN model is capable of predicting IMF_1 for the year (n +1). In Table 5, the standard deviation $\sigma_y(e)$ of the errors is constructed on the training period data is shown along with the correlation coefficient (CC) between the actual IMF_1 and the GRNN results. It is observed that GRNN is quite versatile in capturing the latent nonlinear structure evidenced by the high correlation (0.8062) between the actual and simulated IMF_1 values. An advantage of this approach is that the error in the model can also be characterized statistically.

Table 5. Statistics of GRNN model for IMF: training period (1871–2000)

Region	$\sigma_y(e)$	Correlation Coefficient (CC)
GWB	2.2125	0.806153

* GWB: Gangetic West Bengal

7. Forecasting

The successful modeling of IMF_{1j} and y_j can be extended by one year, to make a forecast of the next year rainfall value. Firstly, for y_{n+1} and then for $IMF_{1,n+1}$is computed from the models mentioned above. The sum of the two values produces a forecast for $R_{n+1.}$ Here, the performance of the forecast strategy is investigated by considering for the period 2001–2013, that was deliberately left out of the modeling exercise. The quality of modeling R_j in the training period (1875–2000) and the efficiency of one-step-ahead forecasting in the testing period (2001–2013) are presented in Table 6.

Table 6. Performance of the modeling and forecasting strategy

Region	Modeling period (1871–2000)			Forecasting period (2001–2013)		
	$\sigma_m(e)$	CC_m	PP_m	$\sigma_f(e)$	CC_f	PP_f
GWB	2.06158	0.7060	0.7321	2.3562	0.8919	0.7499

* GWB: Gangetic West Bengal

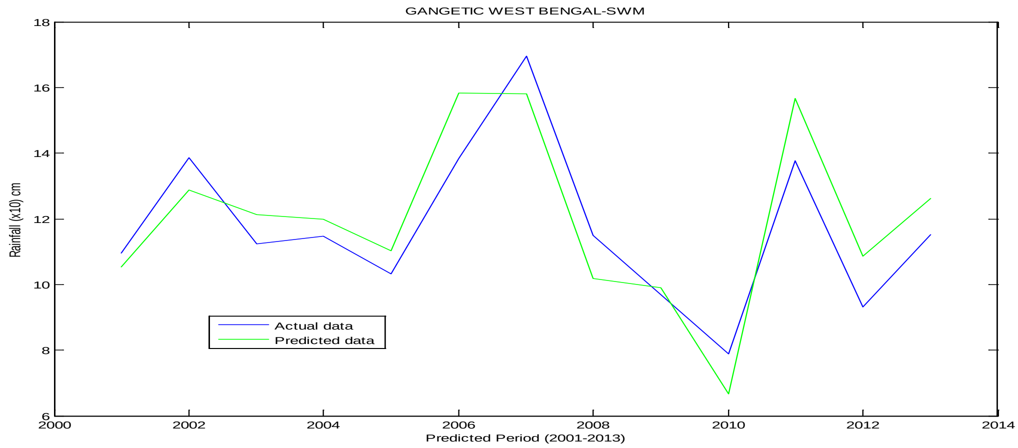

Figure 13. The actual SWM rainfall and Predicted SWM rainfall of GWB for the testing period (2001-2013)
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The sample forecast is an expected value and may be slightly deviate from the actual observation. In Table 7, detailed numerical results on the independent forecasts are presented. Fig. 13 elaborates the actual rainfall data and predicted rainfall data for testing period (2001-2013).

It is evidenced that the present strategy for forecasting SWM rainfall one year ahead, works well within *certain limits*. It may be noted that the sample forecast is an expected value and hence may not precisely match with the actual observation.

Table 7. Independent test forecasting (Gangetic West Bengal)

Year	Actual(x10)cm	Forecast(x10)cm)
2001	10.9499	10.5282
2002	13.8459	11.1995
2003	11.2329	14.3479
2004	11.4639	12.0564
2005	10.3210	12.7563
2006	13.8490	15.5299
2007	16.9519	16.9519
2008	11.5039	10.1950
2009	9.6949	9.8957
2010	7.8919	6.6618
2011	13.7800	15.6741
2012	9.3190	10.8719
2013	11.5200	13.5200

8. Performance of the model

The performance of the model proposed are worked out with three statistical parameters are chosen. The first two are the Root Mean Square Error (RMSE) and the correlation coefficient (CC_m) between the given data and the simulated values out of the model. A statistic called *Performance Parameter* [4], namely, PPm = $1 - (\sigma_m^2)/(\sigma_d^2)$, where σ_m^2 is the mean square error and σ_d^2 is the actual data variance, has also been extracted. In a perfect model, σ_m^2 will be zero and both CC_m and PP_m would tend towards unity. Table 6 indicates that the efficiency of the present model is good for testing period and correlation coefficient between forecasted and actual data is 0.89, which is sufficiently high. In verifying the ability of the model for the forecasting, period 2001–2013, the model parameters are kept constant all through the thirteen years there by relaxing the constrains for forecasting exercise, the model parameter have to be updated, every year before forecast. It is observed that even under the less than ideal condition, the forecasts produced by the model are good enough. For a sample size of N = 13 (2001 - 2013), the correlation coefficient (CC_f) in the test period has to be at least 0.6 to be taken as significant. It is found from Table 6 that CC_f is well above 0.6.

9. Discussion

IAV of monsoon rainfall of GWB has been investigated in this paper with a valuable perspective and points out some interesting feature. It is identified that the seasonal SWM rainfall time series of GWB can be decomposed into eight statistically almost uncorrelated modes; the summation of which gives back the original data. The seventh and eighth modes are identified easily associated with the climatic variation persistent over the total data base. The remaining six empirical modes (IMFs) are narrow band random processes, with well defined central periods, connected to specified well defined meteorological phenomenon. The first IMF which accounts for the highest variability is strongly non–Gaussian and can be successfully predicted using GRNN techniques. The remaining part of the rainfall after removing the first IMF is agreeable for a linear multiple regressive representation. With two decided separate representations; a methodology has been developed to forecast rainfall. However, the analysis does not account for other variability, namely, intra annual, inter seasonal or intra seasonal variability persistent in the monsoon rainfall. The forecast of SWM rainfall for GWB for the year 2012 and 2013 are108.71 cm and 126.21 cm respectively corresponding to the actual SWM rainfall of 93.19 cm 115.20cm, which are within one standard deviation of mean rainfall. Among the first six IMFs, it has been identified that first three IMFs contributed nearly 90% of the variability. It may be interpreted that if those are simultaneously negative, the chances of drought are high. For flood like situation those are highly positive which are in agreement with [15].

10. Conclusion

IAV of GWB has been investigated with an innovative point of view in the current paper. It is established that SWM rainfall time series, sampled annually, is decomposed into eight statistically orthogonal modes; sum of the modes gives back original data to an accurate level. Seventh and eighth modes are associated with the overall climatic variation whilst the remaining six empirical modes are associated with narrow-band random processes having specified central periods and are connected to important meteorological phenomenon parameters. The approach indicates that first mode IMF_1 accounting for highest variability, is strongly non-Gaussian and is modeled by GRNN technique; whereas the remaining part of the rainfall is amenable for linear auto-regressive representation is an interesting approach. The combination of two techniques completes the forecasting exercise of the rainfall prediction is developed for GWB. The particular approach is general enough and efforts are on to include the analysis in other regions of India.

Acknowledgement

The author sincerely thanks National Data Centre, ADGM (R) Pune for providing SWM rainfall data of the Gangetic plains of West Bengal, India.

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