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RECOGNITION OF PHYSICALLY CONNECTED INDEPENDENT CLIMATE VARIABLES FOR SEASONAL MONSOON RAINFALL AND FUTURE FORECAST THROUGH ANN

Research Article

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MODELING OVER REWA DISTRICT

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ABSTRACT

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Key Words:

Neural Network, Monsoon Rainfall, Forecasting, Climate Variables, Modeling. Dependency of seasonal long range rainfall (in mm.) with parameters of climate variables such as Sun Spot Number, Cosmic Ray Intensity, Geomagnetic indices, Maximum Temperature, Minimum Temperature, Maximum Relative Humidity, Minimum Relative Humidity, Wind Speed, are examined over Rewa District. Wherein, merely Cosmic Ray Intensity, Geomagnetic indices, Minimum Temperature, and Maximum Temperature, have found physically connected with monsoon rainfall for long period while, Sun Spot Number, Relative Humidity, and wind speed are not providing any influence. Thus an ANN Modeling to forecast future monsoon rainfall over this region is established through these physically connected independent parameters. It is found that ANN modeling was performance up to 74% and 73% accuracy during training and testing period respectively. The skeleton of entire ANN modeling and its performances are presented through this research paper.

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INTRODUCTION

Identification of physically connected climate variables those are independent to regional specific with monsoon rainfall is a challenging task however may possible (Basu & Andharia, 1992). The modeling to establish relationship between them is an equally vital challenging operational task world widely (Rajeevan 2001; Rajeevan et al., 2004). In this study, relationship between them was established through Neural Network and found good results is presented through this research paper. The paper constructed in the form of Sections. Region of study and data preprocessing to identify physically connected data with rainfall is discussed in the Section I. Modeling of Neural Network to make relationship between rainfall and its physically connected parameters is presented in the Section II. Performance of the Neural Network model in training period and testing period is presented in Section III and IV respectively. Finally in Section V, findings are concluded.

REGION OF STUDY AND DATASET

Rewa lies between 24^0 18' and 25^0 12' N latitudes and 81^0 2' and 82^0 18'. The district is bounded on the North by Uttar

Pradesh, on the East and southeast by Sidhi, on the south by Shahdol, and on the west by Satna. It is part of Rewa Division and has an area of 6,240 km² is depicted in the Fig 1. For this region 40 years data time series of 57 parameters of climate variables of this region was in under study. The climate variables are Sun Spot Number (SSN), Cosmic Ray Intensity (CRI), Geomagnetic indices (AP), Maximum Temperature (TMAX), Minimum Temperature (TMIN), Maximum Relative Humidity (RHMAX), Minimum Relative Humidity (RHMAX), Wind Speed (WS).

To get physical connectivity with total monsoon rainfall (TMRF) the parameters of climate variables such as SSN1, SSN2, SSN3, SSN4, SSN5, SSN1-5, SSN45, CRI1, CRI2, CRI3, CR4, CRI5, CRI1-5, CRI45, AP1, AP2, AP3, AP4, AP5, AP1-5, AP45, TMAX1, TMAX2, TMAX3, TMAX4, TMAX5, TMAX1-5, TMAX45, TMIN1, TMIN2,TMIN3, TMIN,TMIN5, TMIN1-5, TMIN45, RHMAX1, RHMAX2, RHMAX3, RHMAX4, RHMAX5,RHMAX1-5, RHMAX45, RHMIN1, RHMIN2, RHMIN3, RHMIN4, RHMIN5, RHMIN1-5, RHMIN45, WS1, WS2, WS3, WS4, WS5, WS1-

5, WS45 are examined in terms of correlation coefficient with TMRF for the long period of 1976-2016 (40 years).



Fig 1 Rewa district (Study region)

It is found that only 14 climate parameters are such as CRI2, CRI5, AP1, AP2, AP3, AP4, AP5, AP1-5, AP45, TMAX3, TMIN3 TMIN5 TMIN1-5, and TMIN45 have been found correlated up to the level of 40%-55% as depicted in the Figure 2. Thus these parameters are considered to be inputted to observe targeted parameter TMRF in the neural network modeling. Here P1 indicating climate variable P for the month of January, P1-5 indicating average value of climate variable 'P' for the month of January to May etc. In this experiment initial 30 years (1976-2006) time series data were utilized to train while remaining 10 years (2007-2016) data time series were used to test the ANN model.

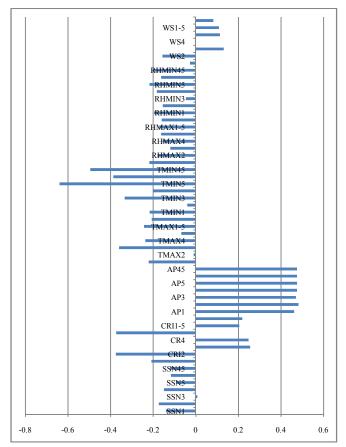


Fig 2 Physically connected input climate parameters with TMRF.

ANN MODELING

Modeling of ANN is dynamic process based on inputted dataset. To get optimum architecture of ANN is a vital challenge for a scientist. Because for this getting optimum parameters of ANN for a case is pre-requisite (Rumelhart et al, 1986). Basically ANN architecture parameters are number of input vectors (n), number of neurons in hidden layer (p), number of neurons in output layer (m), learning rate (α), momentum factor (μ) and number of epochs (e) for the training to get global minima. They have highly impacts on performance of ANN modeling (Karmakar et al., 2014). In this study n = 9 and m = 1 was fixed. However, p, a, and μ were optimized by five set of experiments with 100 epochs and with different set of weights and biases. The brief results are given in the following Table 1. Here for each experiment corresponding model error i.e., mean square error (MSE) were examined for p = 2 to 20, $\alpha = 0.1$ to 0.9 and $\mu = 0.1$ to 0.9. Values corresponding to fourth experiment were found optimum in this case. Fundamentally, α must be closure to 0.1 and μ must be closure to 0.9 (Rumelhart *et al*, 1986). The fourth experiment was found satisfies this condition thus architectural parameters corresponding to fourth experiment was selected for the modeling and training/testing ANN in this case as depicted in the Figure 3. Initial weights and biases was chosen randomly as given in the Table 2.

Table 1 Optimization of ANN parameters.

Exp No	n	p optimum		(2 optimum	µ optimum		
		р	MSE	α	MSE	μ	MSE	
1	14	2	0.005093056992 569648	0.11	0.0050771009 94917843	0.12	0.0050282824 26125972	
2	14	2	0.005076859423 915677	0.11	0.0050728019 24764279	0.12	0.0050285654 45750534	
3	14	2	0.005091429880 160285	0.11	0.0050766114 64492248	0.25	0.0050350473 5453977	
4	14	2	$0.005085430422\\619944$	0.11	0.0050767316 92891875	0.46	0.0050448226 76443782	
5	14	2	0.005088758012 86991	0.11	0.0050758589 58203417	0.26	0.0050343562 3350043	

 Table 2 Initial set of weights, hidden layer biases, and output layer bias.

layer	olub.
A. Weights in hidd	en layer V[i][j], s.t.,
i=114	& j=12
v(i,1)	v(i,2)
0.38987	0.41213655
0.3436165	0.12379342
0.50604624	0.40488654
0.021864057	0.40073854
0.7878052	0.8459872
0.44002116	0.9657862
0.0856626	0.07762629
0.91540724	0.47263914
0.7812143	0.35360605
0.84730107	0.19943357
0.21093363	0.7642921
0.34565765	0.8170283
0.14066994	0.55331993
0.82247466	0.15931296
B. Biases in hidde	en layer Vo(j); j=2
$v_{o}(1)$	$v_o(2)$
0.29380685	0.5346472
C. Weights in out	out layer W(j); j=2
W(1)	W(2)
0.9303065	0.8847912
Bias in output la	yer(Wo) := 0.5

Optimum model as depicted in the Figure 3 was trained with e = 2500000 epochs and minimized MSE is depicted in the

following Figure 4. Processing was taken three days of processing time i.e., 72 Hrs with Pentium 4core processor with 3GB RAM machine. After processing the trained weights and biases are shown in the Table 3. Wherein MSE = 0.0017835888800478675 was minimized and considered as global minima as shown in Figure 4. In this point model was considered to be trained and its performance was examined during testing period.

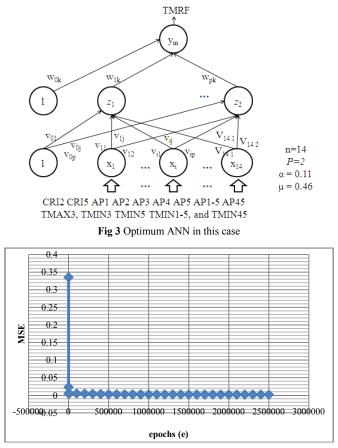


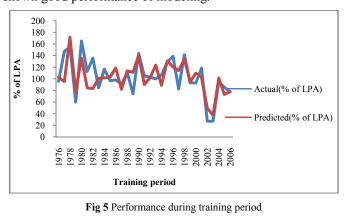
Fig 4 MSE minimization during the training process

Table 3 Trained weights and biases with e = 2500000 epochs and at MSE = 0.0017835888800478675.

A. Weights in hidden layer V[i][j], s.t., i=114 & j=12						
V(i,1)	V(i,2)						
5.608897258	-11.40736741						
-13.51435397	1.298513772						
8.305403986	3.145870292						
-4.304224592	8.479490682						
10.9998589	2.817938858						
-2.721914271	2.790920356						
4.498797072	-9.399378699						
0.847423006	3.335027939						
-7.051523962	2.443566818						
-3.707855632	-5.834558391						
2.18028861	6.137156172						
-24.53302805	8.368867217						
15.66081176	-1.338211225						
10.53051308	-6.176921333						
Updated weights V	/0[i]. s.t., i=2						
Vo(1)	Vo(2)						
4.91133E-05	-3.43221E-05						
Updated weights W[i], s.t., i=2							
W(1)	W(2)						
-22.05547246	8.963316122						
Bias in output layer (Wo) : = -							

PERFORMANCE IN TRAINING

First forty years (1976-2006) data set of independent climate parameters are inputted to observe TMRF as output/target. The performance of the network was accepted due to hypothesis MAD (% of mean) = 6.905790262246053 is less or at least half of the SD (% of mean) = 14.38131091281091. The performance is shown in the Table 4 and Figure 5. It is observed that correlation coefficient between actual and predicted as given in the Table 4 is 0.74 this means model was trained with accuracy level 74% between actual and predicted during tainting period. Deviation between actual and predicted values is depicted in the Figure 6. It is clear that the deviation more than 30% of LPA are found for vary few years. These facts are shown good performance of modeling.



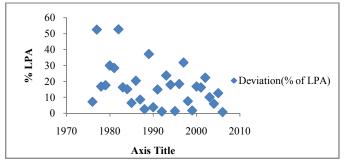


Fig 6 Deviation between actual and predicted values during training period

PERFORMANCE IN TESTING

Second 10 years (2007-2016) data set of independent climate parameters are inputted to observe TMRF as output/target independently in the trained model (i.e., trained weights and biases). The performance is shown in the Table 5 and Figure 7. It is observed that correlation coefficient between actual and predicted as given in the Table 5 is 0.73, this means that model was trained with accuracy level 73% between actual and predicted during testing period as well.

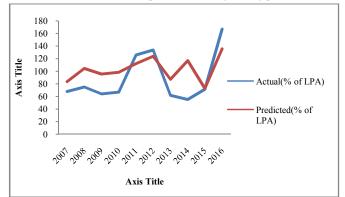


Fig 7 Performance during testing period

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CONCLUSIONS

Modeling of climate variable like forecasting long range monsoon rainfall is one of vital challenging task for meteorologist.

testing period. Training was successful shown that the MAD (% of mean) = 6.905790262246053 is less or at least half of theSD (% of mean) = 14.38131091281091. It is also observed that correlation coefficient between actual and predicted was 0.74.

	Table 4 Performance during training period.									
Year	Normalized Actual	Normalized Predicted	Normalized Absolute Deviation	Actual	Predicted	Deviation	Actual (% of LPA)	Predicted (% of LPA)	Deviation (% of LPA)	
1976	0.467727134	0.481891	0.014164	833.5	896.1	62.6	95.7	102.9	7.2	
1977	0.555247207	0.466269	0.088978	1283.8	827.2	456.6	147.4	95	52.4	
1978	0.565543071	0.587103	0.02156	1348.7	1495.1	146.4	154.9	171.7	16.8	
1979	0.384133084	0.42839	0.044256	522.9	676	153.1	60	77.6	17.6	
1980	0.579012858	0.53746	0.041553	1438.4	1178.5	259.9	165.2	135.3	29.9	
1981	0.500082088	0.44349	0.056592	981.6	733.8	247.8	112.7	84.3	28.4	
1982	0.537936267	0.440686	0.09725	1181.2	722.9	458.3	135.6	83	52.6	
1983	0.444419103	0.478284	0.033865	737.5	879.8	142.3	84.7	101	16.3	
1984	0.507122046	0.479352	0.02777	1016.4	884.6	131.8	116.7	101.6	15.1	
1985	0.469350412	0.482055	0.012704	840.5	896.8	56.3	96.5	103	6.5	
1986	0.472704446	0.51038	0.037675	855.1	1032.8	177.7	98.2	118.6	20.4	
1987	0.457025678	0.438256	0.01877	788.4	713.4	75	90.5	81.9	8.6	
1988	0.496985215	0.501645	0.00466	966.6	989.2	22.6	111	113.6	2.6	
1989	0.419557758	0.497002	0.077444	643.6	966.7	323.1	73.9	111	37.1	
1990	0.549855865	0.544229	0.005626	1251	1217.6	33.4	143.6	139.8	3.8	
1991	0.485902414	0.456168	0.029735	914.4	784.9	129.5	105	90.1	14.9	
1992	0.482142857	0.479975	0.002168	897.2	887.4	9.8	103	101.9	1.1	
1993	0.476151563	0.518803	0.042651	870.3	1076.4	206.1	99.9	123.6	23.7	
1994	0.488943901	0.453049	0.035895	928.5	772.1	156.4	106.6	88.7	17.9	
1995	0.52794357	0.530137	0.002193	1125.4	1137.4	12	129.2	130.6	1.4	
1996	0.542586751	0.513284	0.029302	1208	1047.7	160.3	138.7	120.3	18.4	
1997	0.439149054	0.502549	0.0634	716.9	993.7	276.8	82.3	114.1	31.8	
1998	0.546858142	0.535507	0.011351	1233.1	1167.4	65.7	141.6	134	7.6	
1999	0.461966605	0.465736	0.003769	809	825	16	92.9	94.7	1.8	
2000	0.461966605	0.494567	0.0326	809	955	146	92.9	109.7	16.8	
2001	0.51048951	0.481224	0.029265	1033.4	893	140.4	118.7	102.5	16.2	
2002	0.279971624	0.35411	0.074139	236.8	431	194.2	27.2	49.5	22.3	
2003	0.279971624	0.315512	0.03554	236.8	324.6	87.8	27.2	37.3	10.1	
2004	0.467564259	0.479396	0.011832	832.8	884.8	52	95.6	101.6	6	
2005	0.446564885	0.417709	0.028856	746	636.9	109.1	85.7	73.1	12.6	
2006	0.427631579	0.429462	0.001831	673.2	680	6.8	77.3	78.1	0.8	

Table / Performance during training period

LPA (Long period average of 40 years)

Table 5 Performance during testing period

Year	Normalized Actual	Normalized Predicted	Normalized Absolute Deviation	Actual	Predicted	Deviation	Actual (% of LPA)	Predicted (% of LPA)	Deviation (% of LPA)
2007	0.404750269	0.441663	0.036913	591.4	726.7	135.3	67.9	83.4	15.5
2008	0.422228547	0.484148	0.061919	653.3	906.3	253	75	104.6	29.6
2009	0.395293417	0.489367	0.094073	559.4	930.5	371.1	64.2	95.8	31.6
2010	0.402091208	0.467175	0.065084	582.3	831.1	248.8	66.9	98.4	31.5
2011	0.522652453	0.480536	0.042116	1096.8	889.9	206.9	125.9	112.2	13.7
2012	0.535025768	0.468644	0.066382	1164.7	837.4	327.3	133.7	123.9	9.8
2013	0.389228763	0.450291	0.061062	539.4	760.9	221.5	61.9	87.4	25.5
2014	0.370997728	0.426932	0.055934	481.6	670.6	189	55.3	117	61.7
2015	0.413633738	0.522168	0.108534	622.4	1094.2	471.8	71.5	72.8	1.3
2016	0.581385757	0.448065	0.133321	1454.8	752	702.8	167	135.9	31.1

In this study ANN modeling for long range monsoon rainfall over Rewa district was in under study. 14 climate variables have been found chose are physically connected with monsoon rainfall over the study region, while 57 parameters were examined. ANN modeling with these 14 climate parameters are chosen as input parameter to observe monsoon rainfall as target. Parameters of ANN such as model number of input vector n = 14, number of hidden layer neurons p = 2, learning rate $\alpha = 0.11$ and finally momentum factor $\mu = 0.46$ were most favorable in this case. ANN model with these parameters were trained by 2500000 epochs wherein mean square error decreased up to the 0.0017835888800478675 level. The trained model was shown good result in training as well as

Similar result was also found during testing period as well. The correlation coefficient between actual and predicted was 0.73. One the basis these results it was concluded that the ANN modeling for forecast of monsoon rainfall was quit suitable for this smaller region district Rewa., MP. India. Furthermore more training of ANN may produce better result as well.

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