Meteorol Atmos Phys 101, 93–108 (2008)
DOI 10.1007/s00703-008-0335-2
Printed in The Netherlands

Meteorology and Atmospheric Physics

India Meteorological Department, Shivajinagar, Pune, India

Long lead monsoon rainfall prediction for meteorological sub-divisions of India using deterministic artificial neural network model

P. Guhathakurta

With 10 Figures

Received 26 September 2007; Accepted 30 July 2008
Published online 10 September 2008

Summary

The advantages of artificial neural network technique for explaining the nonlinear behavior between the inputs and output is explored to forecast the monsoon rainfall of 36 meteorological sub-divisions of India. The model uses the past years of monsoon rainfall data only to forecast the monsoon rainfall of coming year. Monthly rainfall time series data for each of the 36 meteorological sub-divisions constructed by Guhathakurta and Rajeevan (2007) is used for the present study. The model captures well the input-output nonlinear relations and predicted the seasonal rainfall quite accurately during the independent period. All India monsoon rainfall forecasts were generated by using area weighted rainfall forecasts of all the sub-divisions. For the first time the idea of up-scaling is introduced in monsoon rainfall prediction using neural network technique and it is shown that up scaling helps to capture the variability of the all India rainfall better. This helps to predict the extreme years like 2002, 2004 better than the neural network model developed based on single time series of all India rainfall. However, derivation of smaller scale (sub-divisions) forecast model may be more useful than the all India forecast.

1. Introduction

Weather Forecasting (especially rainfall) is one of the most important and challenging operational tasks of Meteorological Services all over the world. Weather prediction is a complicated procedure that involves expertise of multiple specialized fields. Lorenz (1969) separated weather forecasting methodologies into two main branches, viz. numerical modeling and scientific processing (AI) of meteorological data. The widespread techniques used for rainfall forecasting are the numerical and statistical methods. Model developments since its inception are continuous process. Even though, current models of weather forecasting in practice have been developed after sufficient research, efforts to develop finer models in order to have a more accuracy in prediction are still going on.

The dynamical models are based on the system of nonlinear partial differential equations governing the atmospheric system. The physics and dynamics of the atmosphere can be better understood by these sets of governing equations. However, in absence of any analytic solution of this system of nonlinear partial differential equations, the numerical solutions based on approximations and assumptions are considered. Forecasts issued by numerical solutions are having good skills in short to medium range. However, these nonlinear equations are having chaotic behavior and very sensitive to initial conditions. The atmo-

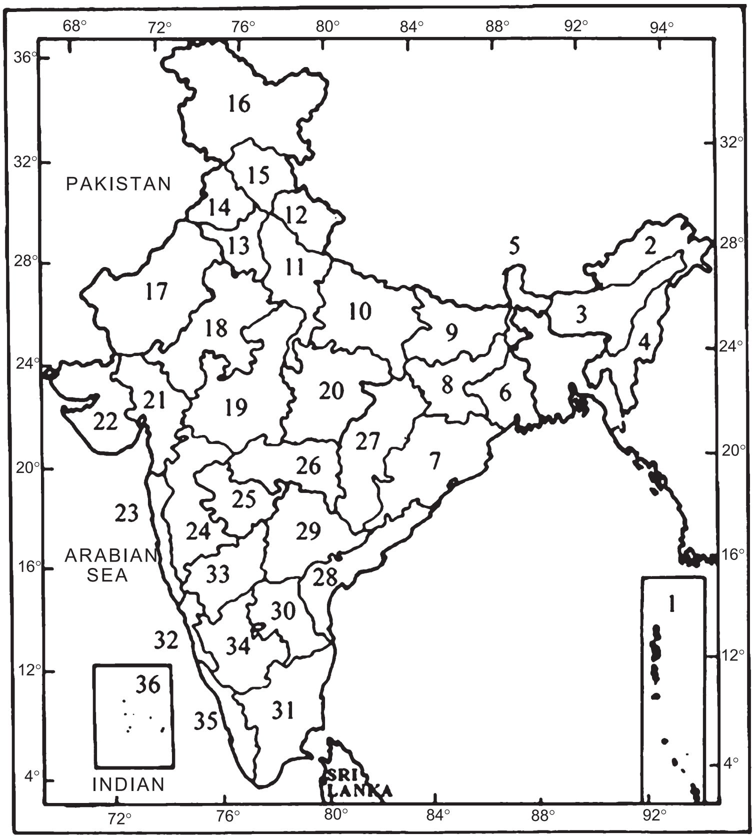
Correspondence: Pulak Guhathakurta, India Meteorological Department, Shivajinagar, Pune 411 005, India (E-mail: pguhathakurta@rediffmail.com)

sphere sets a fundamental limit of the order of two weeks for such deterministic predictions, associated with the rapid growth of initial condition errors arising from imperfect and incomplete observations (WMO 2002). Therefore, only short to medium range weather forecasts issued by numerical solutions have significant skills. But some countries like India where rain fed agriculture plays a crucial role in governing the economy of the country; long range prediction of seasonal rainfall has its own importance. The performances for the long range prediction (greater than two weeks) however, can be improved by using ensemble prediction. Kang and Shukla (2006) examined the potential predictabilities of different numerical models and proposed a multi-model ensemble system by various methods including the signal to noise ratio based on the analysis of variance and the anomaly correlations as an alternative. It was shown that a reasonably good seasonal prediction can be achieved when the multi-model predictions are combined based on the composite of the individual predictions after applying the statistical correction to each separately.

The statistical methods in which rainfall time series are treated as stochastic are widely used for long range prediction of rainfall. India Meteorological Department has been using Statistical Models for predicting monsoon rainfall. Statistical models were successful mostly in those years of normal monsoon rainfall and failed remarkably during the extreme monsoon years like 2002, 2004. Webster et al. (1998) have described the monsoon characteristics in details and also discussed its predictability and prospects for prediction by statistical and dynamical models. Their study observed that though empirical models being used with moderate success, significant success in prediction of monsoon in near future may be expected. The study highlighted that the dynamic processes in the monsoon area are intrinsically chaotic. It is difficult to get a good skill, in predicting the smaller geographical scale like meteorological sub-divisions.

Since 1986 (Rumelhart et al. 1986), the neural network technique has drawn considerable attention from the research workers, as it can handle the complex and nonlinear problems better than the conventional statistical techniques and has successfully applied to a variety of problems. It has a strong potential for pattern recognition and signal processing problems. Moreover it has the ability to predict the future value of the time series from itself. It has been shown by Elsner and Tsonis (1992) that the neural network can be successfully used to predict even the chaotic series as the internal dynamics of the time series can be better classified by the neural network technique. Thus it can overcome the deficiency of usual statistical and dynamical models. Neural network technique is now widely used in weather prediction. Following the neural network forecasts of tropical Pacific wind stress by Tang (1995), Tangang et al. (1997, 1998) forecasted the SSTA in the Niño 3.4 region with neural network models using wind stress as a predictor. Neural network technique is useful both for stochastic and deterministic forecast processes. In deterministic forecast process rainfall time series is treated as deterministic. The attempts to predict all India Southwest Monsoon rainfall using deterministic way were already done by many scientists (Navone and Ceccatto 1994; Goswami and Srividya 1996; Goswami and Kumar 1997; Guhathakurta et al. 1999; Rajeevan et al. 2004). All of them used past years rainfall data to forecast the future rainfall. In spite of getting some accuracy in prediction during the test period, the success was not so appreciable in the operational forecasting.

In the present study most widely used feed forward neural network with back-propagation learning algorithm is used and for the first time an attempt has been made for the monsoon rainfall prediction in sub-division level. The rainfall time series of meteorological sub-divisions (Guhathakurta and Rajeevan 2007) are used for this. The deterministic neural network model which was attempted earlier by Navone and Ceccatto (1994), Goswami and Srividya (1996), Goswami and Kumar (1997); Guhathakurta et al. (1999) is used to learn the internal variability within the time series during the training period and is used to predict future. Finally, prediction for the all India monsoon rainfall, based on the area weighted sub-divisions forecasts has been done and this is compared with the forecast of All India Southwest Monsoon Rainfall (AISMR) separately prepared by using the all India rainfall time series.



1. Andaman & Nicobar Island
2. Arunachal Pradesh
3. Assam & Meghalaya
4. N M M T
5. S H W B & Sikkim
6. Gangetic W. Bengal
7. Orissa
8. Jharkhand
9. Bihar
10. East U P
11. West U P
12. Uttaranchal
13. Har Delhi Chandigarh
14. Punjab
15. Himachal Pradesh
16. Jammu & Kashmir
17. West Rajasthan
18. East Rajasthan
19. West M P
20. East M P
21. Gujarat Region
22. Saurashtra & Kutch
23. Konkan & Goa
24. Madhya Maharashtra
25. Marathwada
26. Vidarbha
27. Chhatisgarh
28. Coastal A P
29. Telengana
30. Rayalseema
31. Tamil Nadu
32. Coastal Karnataka
33. North Interior Karnataka
34. South Interior Karnataka
35. Kerala
36. Lakshadeep

Fig. 1. Thirty-six meteorological sub-divisions of India

2. Data

It may be mentioned that India has been divided in 36 meteorological homogeneous sub-divisions (Fig. 1). Guhathakurta and Rajeevan (2007) have constructed new monthly rainfall series for all the 36 homogeneous meteorological sub-divisions of India using a fixed network of 1476 rain-gauge stations having maximum data availability and a detailed discussion for preparation of this homogeneous data set is given by them. These data are available for the period 1901–2003. These data series along with updated period up to 2005 were taken from India Meteorological Department, Pune. In the present study the data for 1941–2005 has been used. The first 51 years (1941–1991) of data are used for training the network and the data for the period 1992–2005 are used as independent period for verification of the model.

3. Brief description of the neural network techniques

An artificial neural network model is a computational model as in the case of natural neurons. Natural neurons receive signals through *synapses* located on the dendrites or membrane of the neuron. When the signals received are strong enough (surpass a certain *threshold*), the neuron is *activated* and emits a signal through the *axon*. This

Table 1. Neural network model architecture for all the thirty-six sub-divisions. Number of hidden layer is one and number of hidden nodes is three for all the models

Sub-div. no.	NI	LR	MR	MSE	Sub-div. no.	NI	LR	MR	MSE
1	12	0.15	0.15	0.0013	19	12	0.15	0.15	0.0008
2	12	0.15	0.15	0.0010	20	11	0.25	0.25	0.0012
3	12	0.15	0.15	0.0015	21	12	0.15	0.15	0.0013
4	12	0.40	0.40	0.0013	22	12	0.15	0.15	0.0016
5	12	0.15	0.15	0.0016	23	12	0.15	0.15	0.0009
6	12	0.15	0.15	0.0013	24	12	0.15	0.15	0.0008
7	12	0.15	0.15	0.0020	25	12	0.15	0.15	0.0017
8	11	0.30	0.30	0.0010	26	11	0.25	0.25	0.0013
9	12	0.40	0.40	0.0015	27	11	0.40	0.40	0.0015
10	12	0.50	0.50	0.0012	28	12	0.30	0.30	0.0013
11	11	0.20	0.15	0.0012	29	11	0.15	0.15	0.0014
12	11	0.15	0.15	0.0010	30	12	0.25	0.25	0.0013
13	11	0.25	0.25	0.0015	31	11	0.15	0.15	0.0010
14	12	0.10	0.10	0.0015	32	11	0.15	0.15	0.0010
15	12	0.15	0.15	0.0015	33	11	0.30	0.30	0.0015
16	12	0.25	0.25	0.0014	34	12	0.30	0.30	0.0009
17	12	0.15	0.15	0.0010	35	12	0.40	0.40	0.0010
18	11	0.25	0.25	0.0010	36	12	0.10	0.05	0.0014

NI = No. of input, LR = learning rate, MR = momentum rate, MSE = mean square error

signal might be sent to another synapse, and might activate other neurons. The complexity of real neurons is highly abstracted when modeling artificial neurons. These basically consist of *inputs* (like synapses), which are multiplied by *weights* (strength of the respective signals), and then computed by a mathematical function which determines the *activation* of the neuron. Another function (which may be the identity) computes the *output* of the artificial neuron (sometimes in dependence of a certain *threshold*).

A three layer neural network with one input layer, one hidden layer and one output layer is used to develop the model. The transfer function used here is the sigmoidal function and most commonly used "back propagation learning algorithm" is used to train the network. Unlike the use of different predictors, past years monsoon rainfall data is used as input in the model. The advantage of this model is that prediction of future year monsoon rainfall can be available nearly one year in advance. The network is allowed to train until the mean square error reaches a preassign error limit (Table 1). The main problem in neural network is converging of the iterative schemes to local minima. Since back propagation uses a gradient-descent procedure, a back propagation network follows the contour of an error surface with weight updates moving it in the direction of steepest descent. For simple two-layer networks (without a hidden layer), the error surface is bowl shaped, gradient-descent is used to minimize error; the network will always find a minimum error solution (at the bottom of the bowl). Such minimum error solutions are called global minima. However, when an extra hidden layer is added to solve more difficult problems, the possibility for complex error surfaces arises which contain many minima. Since some minima are deeper than others, it is possible that gradient descent will not find global minima rather, the network falls into local minima which represent suboptimal solutions. In such cases there are many approaches to avoid falling in the local minima. An important approach to improve performance is to form ensembles of neural networks. The usefulness and effectiveness of ensembles for the improvement of forecast performances is discussed by Bishop (1995) (also Navone et al. 2001). The member networks' predictions are averaged (or combined by voting) to form the ensemble's prediction. In this study different ensemble runs (five) were followed where in each ensemble a new set of initial random weights was used to train the network in order to get the desired mean square error. Finally an average of all the forecasts from different ensembles runs were used to get the desired forecast. It has been mentioned by Zhang (2007) that relatively small ensemble sizes of 5 and 10 are quite effective in the improvement of forecasting performance.

4. Deterministic neural network model

As mentioned earlier, attempt to apply the neural network technique to reconstruct the assumed deterministic dynamics of the time series data for the all India monsoon rainfall prediction is not new (Navone and Ceccatto 1994; Goswami and Srividya 1996; Goswami and Kumar 1997; Guhathakurta et al. 1999; Rajeevan et al. 2004). In the present study separate 36 neural network models were developed to forecast the South West monsoon rainfall for all the 36 meteorological sub-divisions of India. In all these models immediate past years of data are used to predict the immediately following year South West monsoon rainfall. The models were tried for varying number of inputs starting from 5 to 12 year. However, for more number of inputs, number of required training years will also be more. It has been found that the model with the past 11 to 12 years as input gives better results. Monsoon rainfall time series have periodicity in the range 2–4 years (quasi biennial oscillations) and/or 10–12 years (sunspot cycle). The idea behind including previous 11–12 years of data as input, to train the network is to have characteristic of both the above cycles. Also a separate neural network model was developed using the all India monsoon rainfall series and using immediate past 11 years data for predicting the twelfth year rainfall.

In neural network technique problem of over fitting is often encountered. The process of overfitting of neural network during the training is also known as overtraining. Early stopping is an approach to avoid under-fitting and over-fitting (Sarle 1995) and hence getting good generalization. When further training does not result in better generalization the training is stopped. Due to this Root Mean Square Errors (RMSE) during the training period in some of the sub-divisions are found to be higher than that for the independent period. It may be mentioned that the independent period (1992–2005) is never used while developing/training the model.

5. Sub-division rainfall forecast

Thirty six separate deterministic neural network models were developed for each of the 36 meteorological sub-divisions. Performance of all these models during the independent period is shown in Fig. 2. The RMSEs for all the models during the training period and the independent period (1992–2005) and standard deviation of the monsoon rainfall time series are given in Fig. 3. The RMSEs values for the independent period (1992–2005) are less than the standard deviation for all the sub-divisions except NMMT. This is mainly because of the rainfall 930.5 mm of 2005 which is ever recorded lowest rainfall for this sub-division which the model could not capture. The RMSE was even less than half of the standard deviation values for the fifteen sub-divisions viz. Andaman and Nicobar Island, Arunachal Pradesh, Assam and Meghalaya, Bihar, West U.P., Punjab, Jammu and Kashmir, West Rajasthan, East M.P., Vidarbha, Chhatisgarh, Coastal A.P. Rayalseema, Coastal Karnataka and Kerala. This clearly indicates a noteworthy skill of the models. Furthermore, 17 out of the 36 sub-divisions RMSE during the independent period is less than the RMSE of the training period. Normally when the network is trained to reduce the RMSE in the training period to a sufficiently smaller value over-fitting in the training may occur. However RMSE for the independent period becomes large enough. In this case, network was trained in order to avoid such type of over-fitting. Details of the network architectures for each of the 36 sub-divisions are given in Table 1. The convergence curves in Fig. 4 show how the RMSEs during the training and independent period are converging. The results are shown for six sub-divisions representing different areas of India viz. Assam and Meghalaya, Bihar, West U. P., East Rajasthan, Vidarbha and Rayalseema. The sub-divisions Assam and Meghalaya and Bihar are from eastern parts, the sub-divisions West U. P., East Rajasthan are from the north and western parts of the country which have high co-efficient of variability and the sub-divisions Vidarbha and Rayalseema are from the central and south peninsular India. In each case convergence of the RMSE curve during the independent period is also achieved along with the RMSE curve converging during the training period.

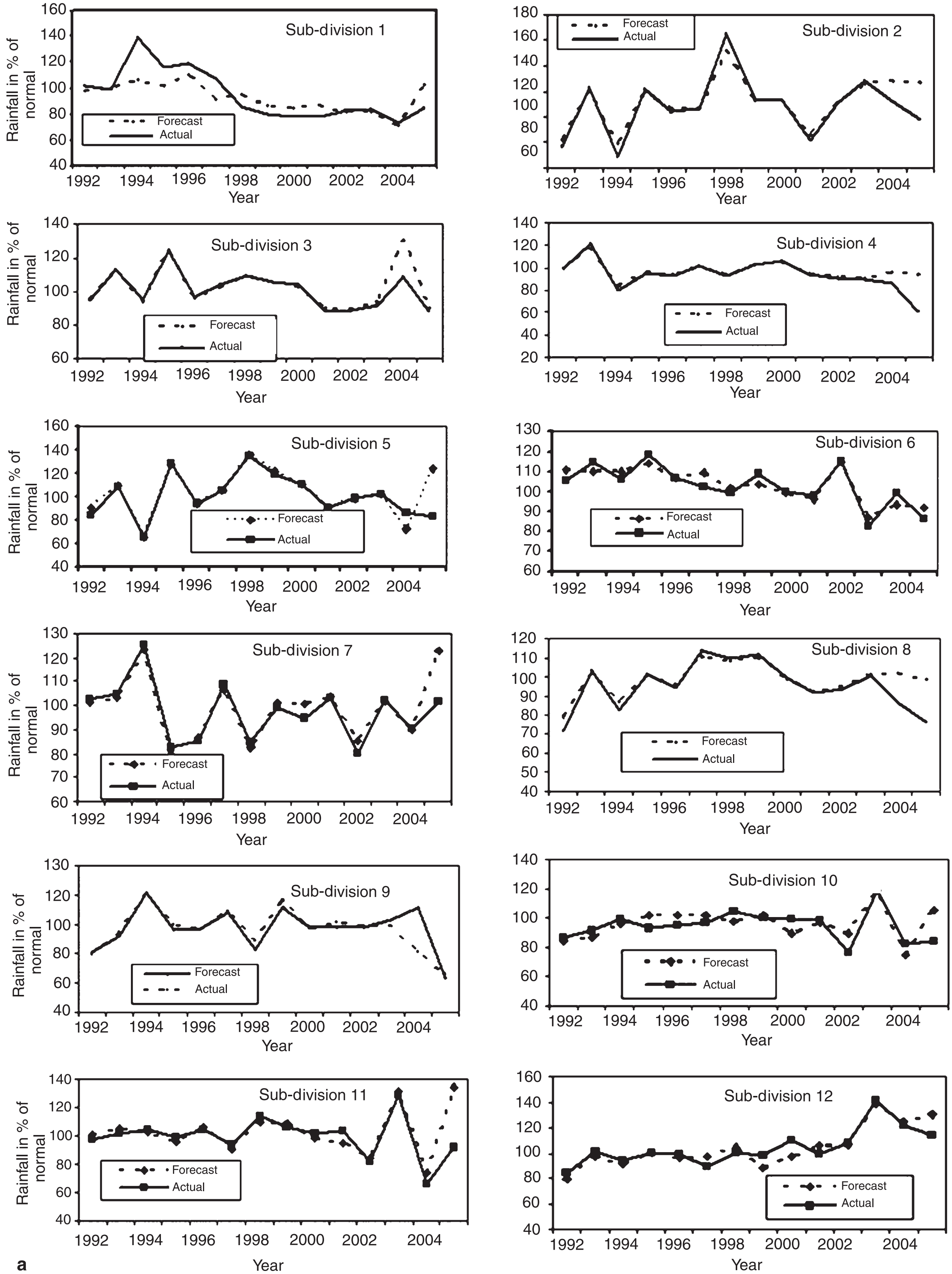


Fig. 2. Performance of the Neural Network models during the independent period (1992–2005) for the (**a**) sub-divisions numbers 1–12, (**b**) sub-divisions numbers 13–24, (**c**) sub-divisions numbers 25–36

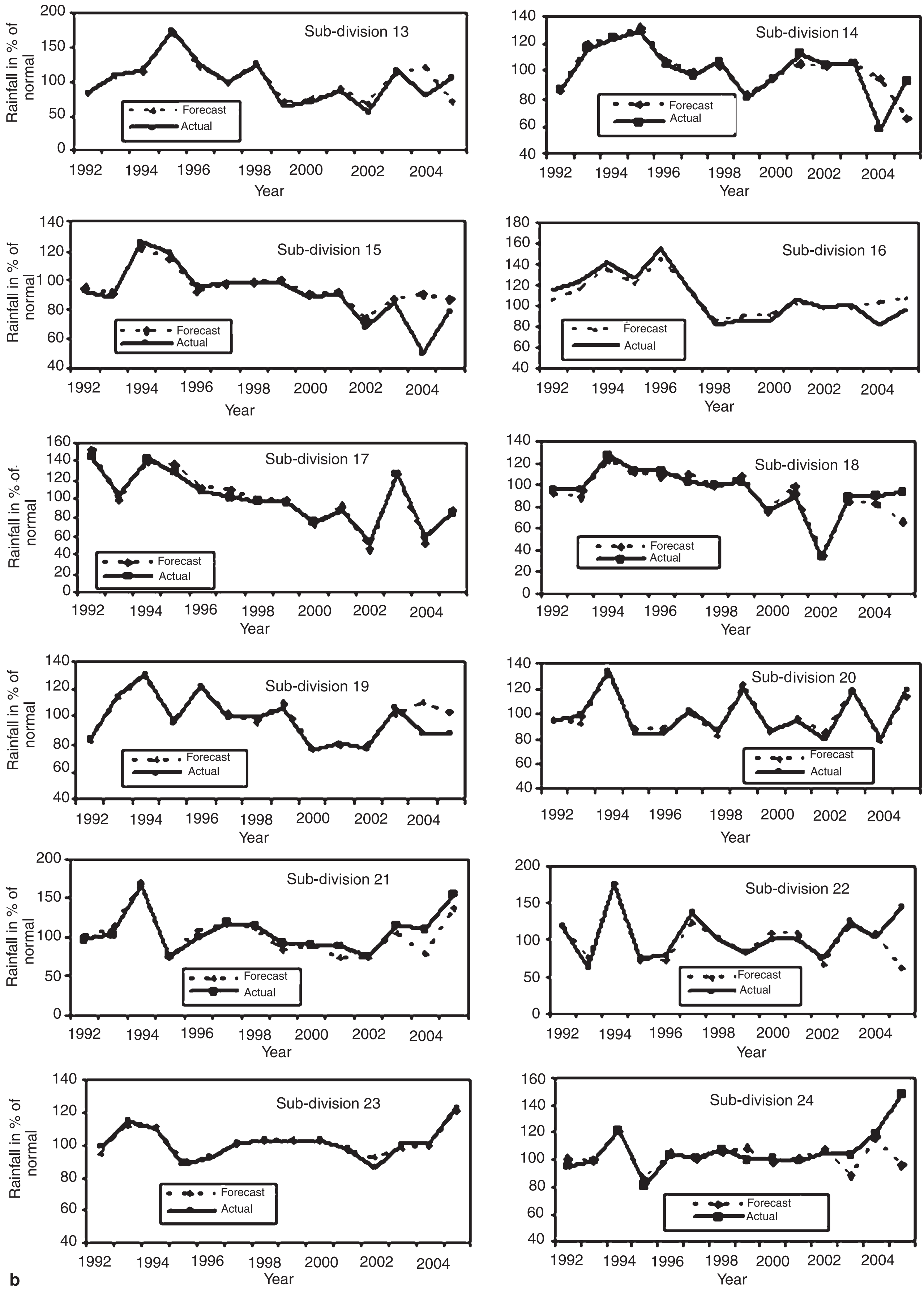


Fig. 2 (*continued*)

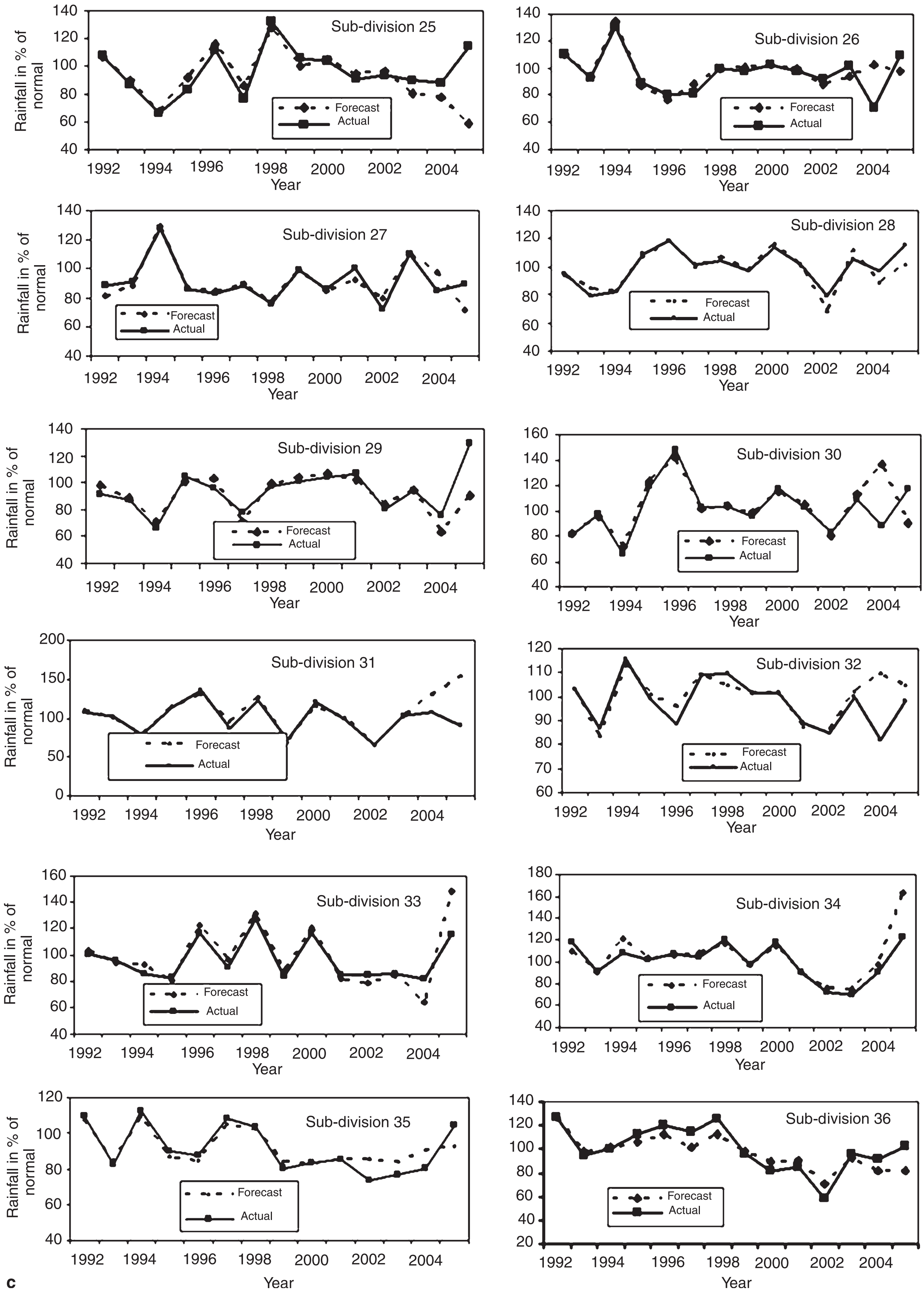


Fig. 2 (*continued*)

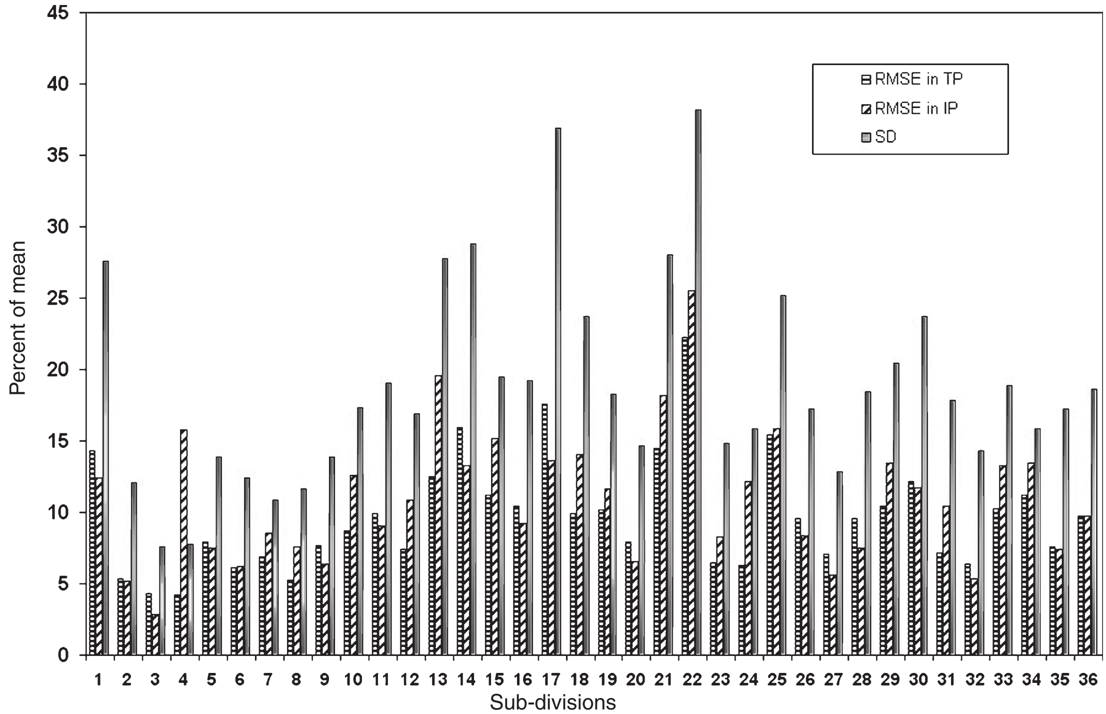


Fig. 3. RMSE for the models during the training period (TP), the independent period (IP) and the standard deviation (SD) (% of mean) of monsoon rainfall for the 36 sub-divisions

These also confirm that in our study the over-fitting does not happen in training the network.

6. All India rainfall forecast

Using area weighted values of the monsoon rainfall forecast of all the 36 sub-divisions; forecast for the all India southwest monsoon rainfall was computed. A separate deterministic neural network model was also developed to forecast the all India southwest monsoon rainfall using the all India SW monsoon rainfall time series. The same methodology used (i.e., to try for different network architecture, i.e. number of input, learning rate and momentum rate to minimize the error during training period) to get optimal model for sub-divisions is followed to get optimal model for all India forecast. However number of input years was not tried beyond 12 years. Figure 5 shows the comparison of RMSEs for the different neural network models during the independent period for the all India forecast. The error decreases as the number of input increases. The lowest RMSE value is obtained when the number of input is 11. Therefore use of past 11 years data as input improves the performance of the model in this case. Thus past 11 years data was used to predict for the 12th year value for the all India model. First 51 years (1941–1991) of data were used for training the network and the data for the period 1992–2005 were used as independent period. The performances of this model as well as from the area weighted sub-division forecasts during the training and independent periods are shown in Figs. 6 and 7, respectively. Comparison of both the forecasts for all India monsoon rainfall made from area weighted sub-division forecasts and forecast from the all India model in standardized anomalies along with actual values during the independent period are shown in Fig. 8. Here standardized anomaly is calculated by subtracting the mean value from the actual value and then dividing by the standard deviation which is mostly used to normalize the data. Both the models are able to predict the deviation of the rainfall from the mean value accurately. However the forecast, made from area weighted values are slightly more closer to the actual than the other and it also able to capture the excess year (1994) and deficient years (2002; 2004) quite accurately. Table 2 gives the error performances during the training and independent period for both the models. The correlation coefficient between the forecast and actual values for the sub-division

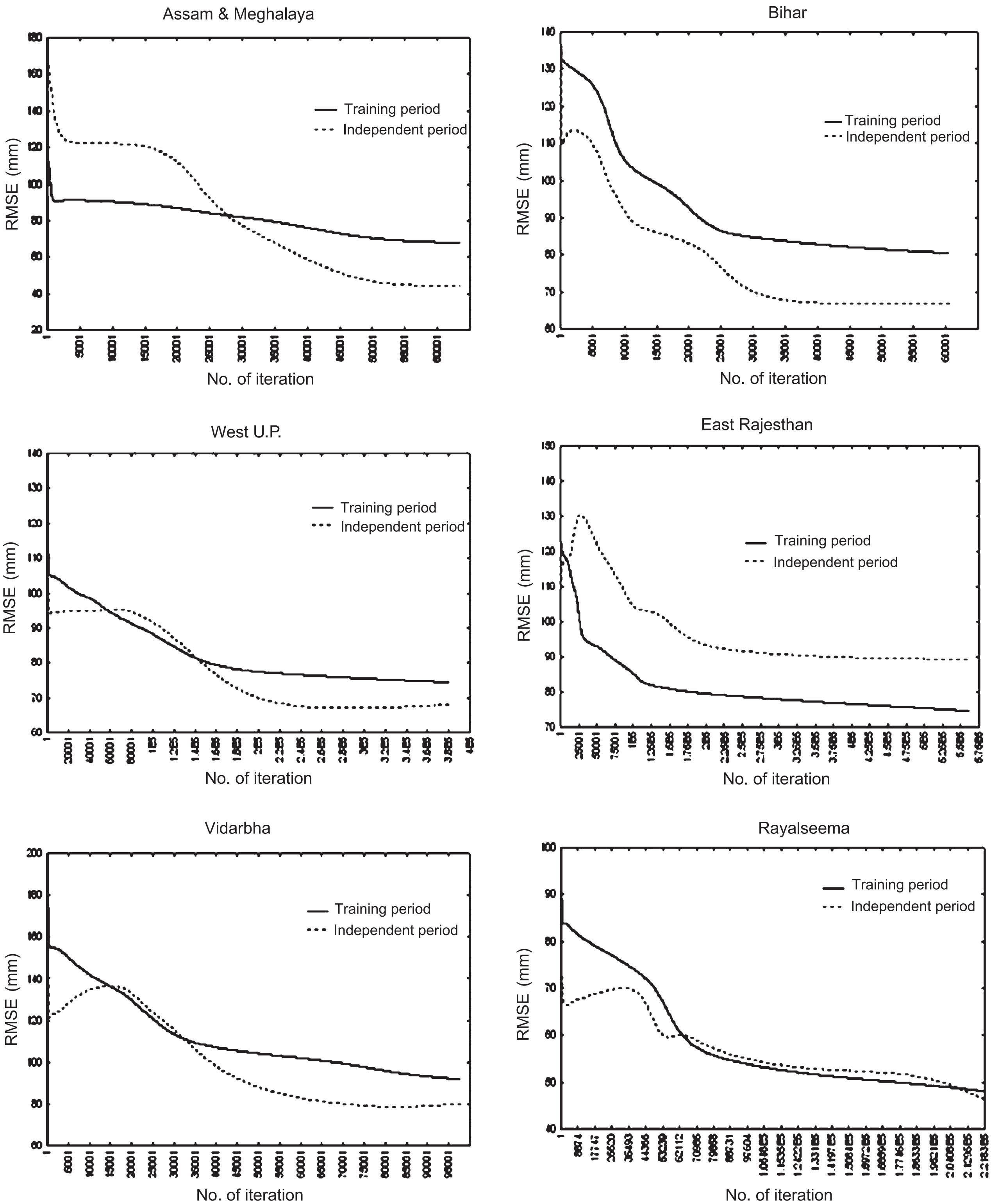


Fig. 4. Convergence curve of the RMSE during the training and independent period for the sub-divisions Assam and Meghalaya, Bihar, West U.P., East Rajasthan, Vidarbha and Rayalseema

area weighted model is 0.9, which again indicates a sound skill of the model. It may be inferred from Table 2 that the RMSE in All India model is quite larger than all India sub-division area weighted model. As mentioned in Sects. 3 and 4 that for all the Neural Network models,

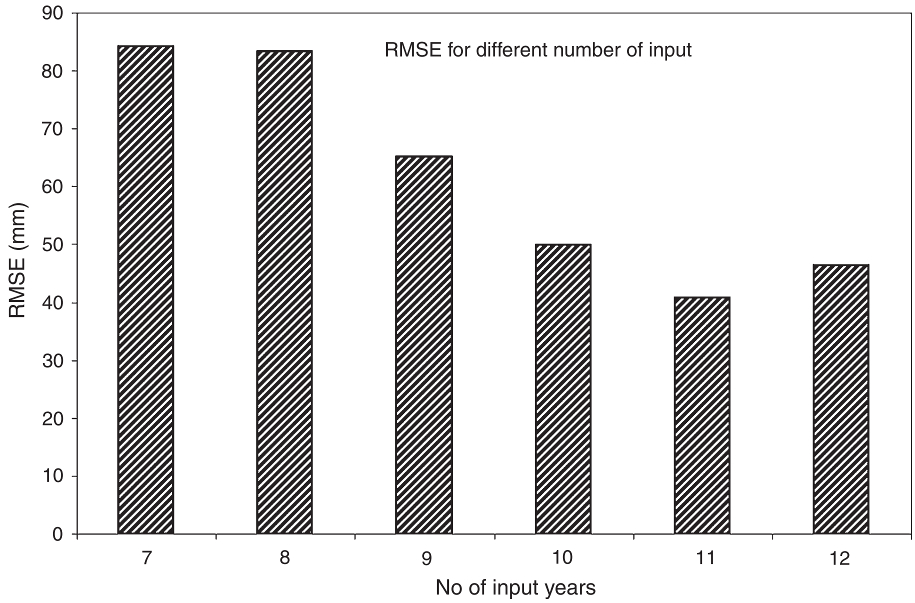


Fig. 5. Comparison of Root Mean Square Error for the all India model for different number of input years

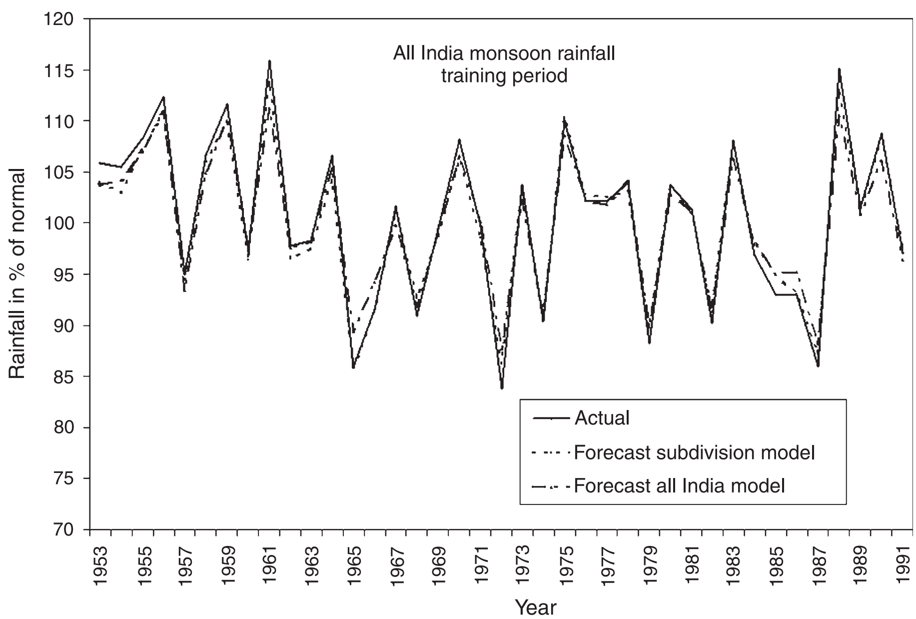


Fig. 6. Performance of the sub-division area weighted model and all India model during the training period

sub-divisions as well as all India, training were continued until the mean square errors reach a priori error estimate. Further training does not result in better generalization. This can be better viewed in Fig. 4 where convergence curves for the training period follow almost parallel path to the X-axis after some iterations. To avoid over-training early stop criteria was used for all the Neural Network models. It may be mentioned that each of the sub-division rainfall series has more inter-annual variability than the all India rainfall series. Therefore each of these sub-division models learned their internal dynamics more closely during their training and thus was able to capture the extreme (excess/deficient) rainfall years for the individual sub-divisions (Fig. 2). In general a smooth time series with less variability should have highest predictability than the series having more variability. Here the smoothed time series is the all India time series and the individual time series having more variability are the rainfall time series of 36 sub-divisions series. The performance of the neural network model based on the all India rainfall series is better than the all India area weighted model of 36 individual models

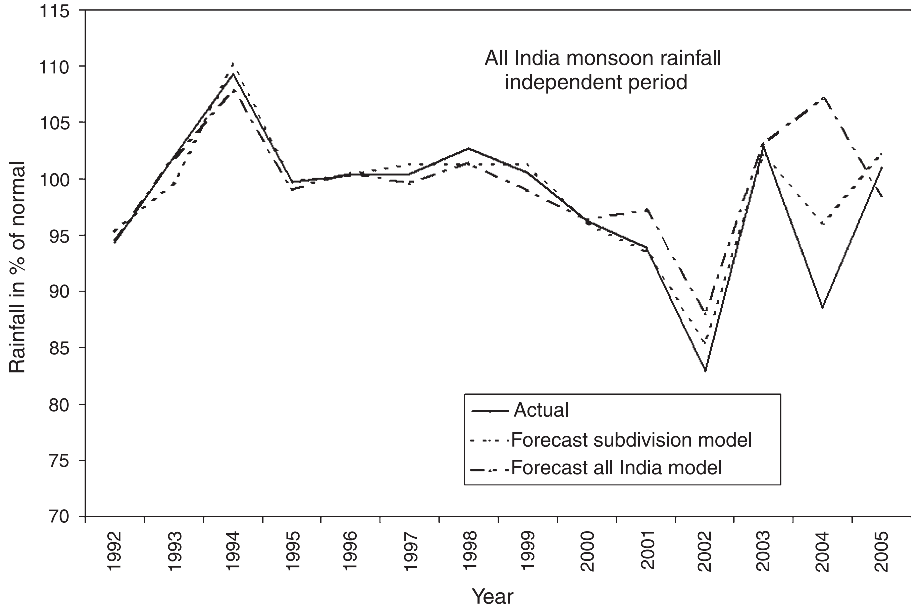


Fig. 7. Performance of the sub-division area weighted model and all India model during the independent period

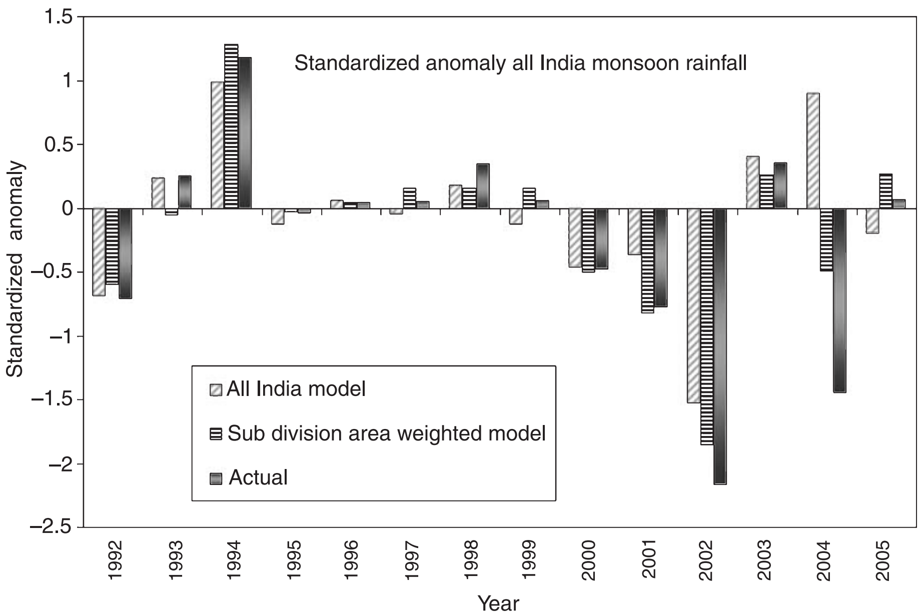


Fig. 8. Standardized anomalies along with actual values of All India SW monsoon rainfall during the independent period (1992–2005)

Table 2. Error performances of the deterministic neural network models using all India rainfall series and all India area weighted forecast of sub-divisions forecasts. Standard deviation of the SW monsoon rainfall of India is 7.9% of normal

Type of model	RMSE				C.C. with actual during independent
	During training period		During independent period		
	In mm	(% of mean)	In mm	(% of mean)	period
All India	16.6	1.9	46.5	5.3	0.6
Sub-division area weighted	11.0	1.2	20.6	2.3	0.9

for the years when the actual or realized rainfall was closer with the normal, i.e. when deviation from normal was less. However for the large excess or deficient years the performance of the neural network model based on the all India area weighted model is better than the neural network model based on the all India rainfall series. From Fig. 8 we find that for the years 1993, 1995–2000, 2003 and 2005 standardized anomaly for the actual/realized rainfall was within ±0.5. RMSE for the all India model and area weighted model for these nine years are 8.3 mm and 10.3 mm respectively. Thus performance of the neural network model based on the all India rainfall series is better than the all India area weighted model for these 9 years. However, for the remaining 5 years, i.e., 1992, 1994, 2001, 2002 and 2004 when deviation of realized rainfall from normal was large, RMSE for the all India model and area weighted model are 76.8 mm and 31.4 mm, respectively. This confirms the superiority of the all India area weighted model over the all India model in the extreme years. In the smoothed series of all India, variability is less and trained neural network model for all India also not performed well for the extreme years. The idea of up-scaling thus helps us to improve quality of the forecast.

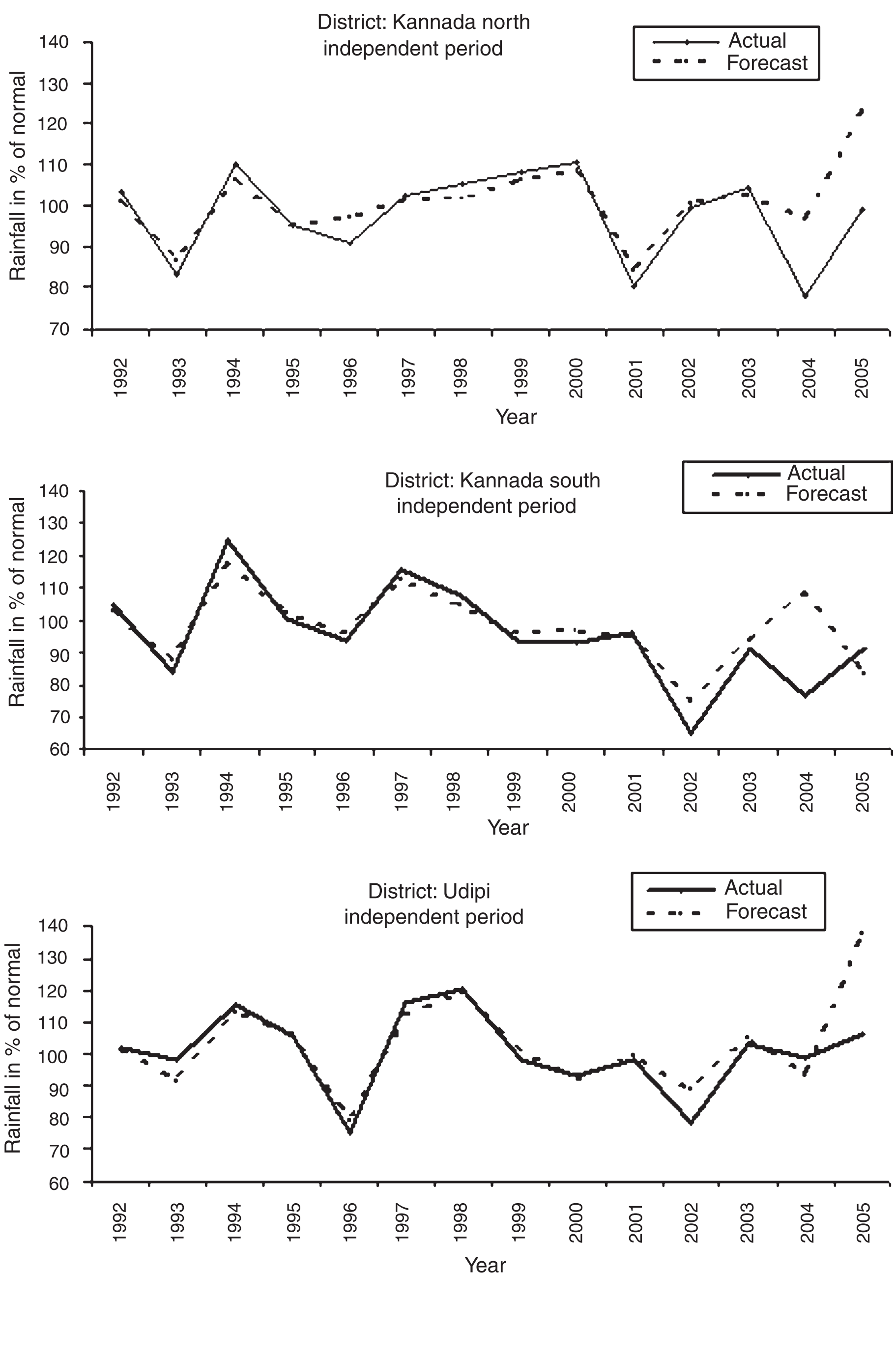


Fig. 9. Performances of deterministic neural network models for the three districts of Coastal Karnataka during the independent period

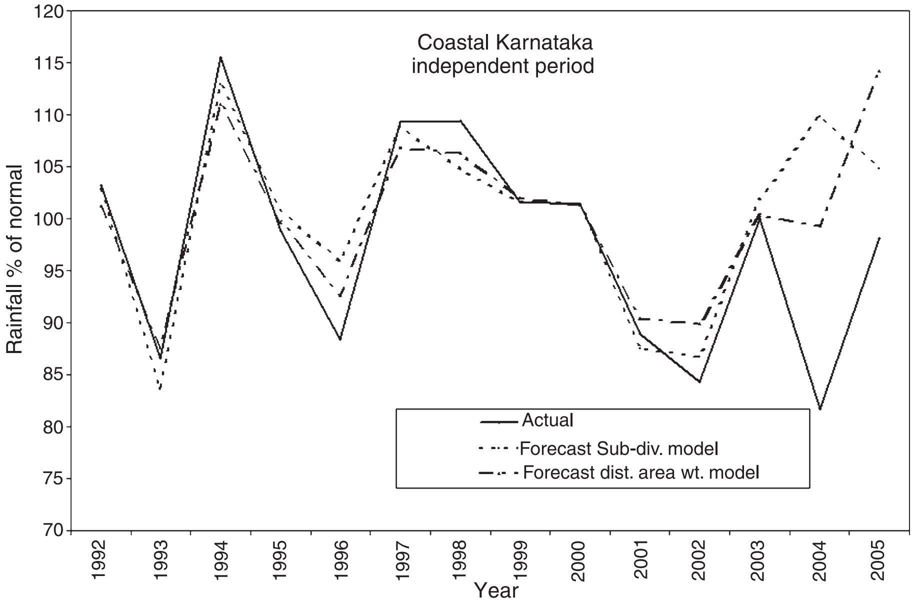


Fig. 10. Comparison of performances of district area weighted and sub-division deterministic neural network models of Coastal Karnataka

8. Future scope

The performance of the model may be further improved if we go for smaller spatial scale. This is the major advantage of the model. In other models (mainly statistical models) going to smaller scale will go against the accuracy of the model. It may be mentioned that the major demands for the long range forecast are from the farmers and for them district level forecast is more useful than the all India forecast or even sub-division forecast. The deterministic neural network model had already been applied for forecasting district rainfall (Guhathakurta 2006). The sub-division Coastal Karnataka is having three districts viz. Kannada North, Kannada South and Udipi. Three separate deterministic neural network models for these three districts were generated. Each of these network models has 12 numbers of input nodes, three hidden nodes. The data for the year 1921–1991 years was used for training the networks and the data for the period 1992–2005 was used as independent period. Performances of these models during the independent period are shown in Fig. 9. Sub-division forecast was then made from the area weighted of district rainfall forecast. Figure 10 gives the performance of this model along with the performance of sub-division model developed using the sub-divisional time series of Coastal Karnataka. The performances of district area weighted model is better than the sub-division model and also RMSE during the independent period now improved to 4.8% of mean compare to 5.35% of mean which is the RMSE of the sub-division model for Coastal Karnataka during the independent period. This clearly highlights that if up-scaling is done from a smaller region the accuracy in the forecast is likely to be improved. However more homogeneous the rainfall time series more improvement in the performances may be attained.

9. Conclusions

In this study, deterministic neural network models for the monsoon rainfall prediction of the smaller spatial scale i.e. sub-division and all India are developed. The performances of these models are encouraging. Moreover, forecasts have a longer lead time as the forecast can be made at the end of previous year monsoon. The method is based on the assumption that the time series is a part of state space representation of a nonlinear dynamical system. Indian monsoon rainfall is a part of global phenomena. Regional as well as global climatic fluctuations modulate it. In the statistical regression model, selected regional and global predictors having strong correlations with the predictand are used for prediction of monsoon rainfall. It would be worthy to assume that rainfall time series itself have all the effect (linear or nonlinear) of these known as well as unknown governing forces. The deterministic method developed in this study explores these internal properties present within the rainfall time series and forecast for the future. This may be one of the reasons for getting a better result than the conventional statistical techniques. It may be mentioned that the present model is able to predict large deficient monsoon rainfall of 2002, large excess monsoon year 1994. This indicates that the indication of deficient/excess monsoon conditions was present in the time series itself. The error statistics shown in Table 3 gives the number of years in Independent period with error ranging in different categories. This helps in identifying the sub-divisions for which performances of the models are better. For the 16 sub-divisions in one out of 14 years error was >30%. Number of cases (year) when error is within 10% varies from 8 (for sub-division 1) to 14 (for sub-divisions 6, 20 and 23).

Table 3. Error statistics for the each of individual sub-divisions during the independent period of 14 years

Sub-div. no.	Number of cases in independent period with error			
	<10%	**10–20%**	**20–30%**	**>30%**
1	8	4	2	0
2	11	2	0	1
3	13	0	1	0
4	12	1	0	1
5	12	1	0	1
6	14	0	0	0
7	13	0	1	0
8	13	0	0	1
9	11	2	1	0
10	12	1	1	0
11	12	1	0	1
12	12	2	0	0
13	11	1	0	2
14	12	0	1	1
15	13	0	0	1
16	12	1	1	0
17	12	2	0	0
18	12	1	1	0
19	12	1	1	0
20	14	0	0	0
21	11	2	1	0
22	9	4	0	1
23	14	0	0	0
24	12	1	0	1
25	10	3	0	1
26	12	1	0	1
27	12	1	1	0
28	12	2	0	0
29	12	1	0	1
30	12	0	1	1
31	12	0	1	1
32	13	0	0	1
33	12	0	2	0
34	12	1	0	1
35	11	3	0	0
36	9	4	1	0

Also, for the first time sub-division rainfall series constructed from a fixed network of 1476 stations (Guhathakurta and Rajeevan 2007) is used to develop the neural network model. We have also found that in contrary to the downscaling, up scaling is perhaps a better way for long range prediction. The apparent reasons behind this as mentioned earlier, are large rainfall variability between the smaller regions and even (sometime) the contrasting rainfall behaviors between the smaller sub-regions which are retained in up scaling but are smoothened out once averaging is done. Even the study can further go to even smaller spatial scale probably up to district level. It is likely we may get more accuracy in predicting sub-divisions and all India monsoon rainfall if up-scaling is done from the district level. District (area normally of 100–1000 square km) can be used as the optimum geometrical scale in developing the model. Also district level forecast is more useful in agriculture or other economical purpose and any disaster management than state/sub-division or all India forecast.

Acknowledgement

The author is thankful to the Director General of Meteorology, India Meteorological Department (IMD) for providing the facilities for the work and permitting to publish the paper in extra-departmental journal. The author is grateful to Shri A.K. Srivastava of IMD for his continuous encouragement and all the staffs of Hydrology Section of India Meteorological Department, Pune for their cooperation in the work.

References

Bishop C (1995) Neural networks for pattern recognition. Oxford University Press, Oxford

Elsner JB, Tsonis AA (1992) Nonlinear prediction, chaos and noise. Bull Amer Meteor Soc 73: 49–60

Goswami P, Kumar P (1997) Experimental annual forecast of all India mean summer monsoon rainfall for 1997 using a neural network model. Current Sci 72: 781–2

Goswami P, Srividya (1996) A novel neural network design for long range prediction of rainfall pattern. Current Sci 70: 447–57

Guhathakurta P (2006) Long range monsoon rainfall prediction of 2005 for the districts and sub-division Kerala with artificial neural network. Current Sci 90(6): 773–9

Guhathakurta P, Rajeevan M (2007) Trends in rainfall pattern over India. Int J Climatol; DOI: 10.1002/joc.1640 2007

Guhathakurta P, Rajeevan M, Thapliyal V (1999) Long rang forecasting Indian summer monsoon rainfall by a hybrid principal component neural network model. Meteorol Atmos Phys 71: 255–66

Kang I-S, Shukla J (2006) Dynamic seasonal prediction and predictability. Chap. 15: The Asian monsoon. Springer Praxis, Chicherster, pp. 585–612

Lorenz EN (1969) Three approaches to atmospheric predictability. Bull Amer Meteor Soc 50: 345–9

Navone HD, Ceccatto HA (1994) Predicting Indian monsoon rainfall: a neural network approach. Clim Dyn 10: 302–12

Navone HD, Granitto PM, Verdes PF, Ceccatto HA (2001) A learning algorithm for neural network ensembles. Inteligencia artificial. Revista Iberoamericana de Inteligencia Artificial 12: 70–4

Rajeevan M, Guhathakurta P, Thapliyal V (2000) New models for long range forecasts of summer monsoon rainfall over North West and Peninsular India. Meteorol Atmos Phys 73(3–4): 211–25

Rajeevan M, Pai DS, Dikshit SK, Kelkar RR (2004) IMD's new operational models for long-range forecast of southwest monsoon rainfall over India and their verification for 2003. Current Sci 86(3): 422–31

Rumelhart D, Hinton GE, Williams RJ (1986) Learning internal representation by error propagation. In parallel distributed processing: exploration in the microstructure of cognition, Vol. I. MIT Press, Cambridge, pp. 318–62

Sarle WS (1995) Stopped training and other remedies for overfitting. Proc. 27th Symposium on the Interface of Computing Science and Statistics, pp. 352–60

Tang B (1995) Periods of linear development of the ENSO cycle and POP forecast experiment. J Climate 8: 582–691

Tangang FT, Hsieh WW, Tang B (1997) Forecasting the equatorial sea surface temperatures by neural network models. Climate Dyn 13: 135–47

Tangang FT, Tang B, Monahan AH, Hsieh WW (1998) Forecasting ENSO events: a neural network-extended EOF approach. J Climate 11(1): 29–41

Webster PJ, Magana VO, Palmer TN, Shukla J, Thomas RA, Yanai M, Yasunari T (1998) Monsoons: Processes, predictability, and the prospects for prediction. J Geophys Res 103: 14451–510

World Meteorological Organization (WMO) (2002) WMO Statement on the scientific basis for, and limitations of, weather and climate forecasting. Abridged report with resolutions. 54th Session of the WMO Executive Council, Geneva, 2002

Zhang GP (2007) A neural network ensemble method with jittered training data for time series forecasting. Inform Sci 177(23): 5329–46