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Markov Chain-Incorporated Artificial Neural Network Models for Forecasting Monthly Precipitation in Arid Regions

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Abstract Forecasting monthly precipitation in arid and semi-arid regions is investigated by feed forward back-propagation (FFBP), radial basis function, and generalized regression artificial neural networks (ANNs). The ANN models are improved by incorporating a Markov chain-based algorithm (MC-ANNs) with which the percentage of dry months is determined such that the non-physical negative values of precipitation generated by ANN models are eliminated. Monthly precipitation data from three meteorological stations in Jordan are used for case studies. The MC-ANN models are compared based on determination coefficient, mean square error, percentage of dry months and additional performance criteria. A comparison to ANN models without MC incorporated is also made. It is concluded that the MC-ANN models are slightly better than ANN models without MC in forecasting monthly precipitation while they are found appropriate in preserving the percentage of dry months to prevent generation of non-physical negative precipitation.

Keywords Artificial neural networks · Intermittent precipitation · Jordan · Markov chain

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الخلاصة

لقد استُخدمت ـ من أجل التنبؤ في الهطول الشهري للمطر في المناطق القاحلة وشبه القاحلة ـ ثلاثة أنواع من الخلايا العصبية الصناعية، الأولى هي الخلايا العصبية ذات التغذية الأمامية ، والانتشار الخلفي (FFBP)، والخلايا العصبية ذات الدالة الاساسية الشعاعية (RBF)، وأخيرا الخلايا العصبية ذات الانحدار العام (GR) للخلايا العصبية الصناعية (ANN). ومن أجل تحسين النتائج تم دمج الخلايا العصبية الصناعية (ANN) مع خوارزمية سلسلة ماركوف (MC-ANNs) من أجل التخلص من قيم الهطول السلبية غير المادية الناتجة عن نماذج الخلايا العصبية الاصطناعية (ANN) ، وذلك بالاعتماد على نسبة الأشهر الجافة. وقد استُخدمت بيانات الهطول الشهرية من ثلاث محطات أرصاد جوية في الأردن. ومن أجل مقارنة النماذج (MC-ANN) تم استخدم معامل التحديد، ومعدل الخطاء التربيعي، ونسبة الأشهر الجافة ومعايير أداء اخرى. وكذلك تمت مقارنة الخلايا العصبية (ANN) غير المدمجة بسلسلة ماركوف (MC). وفي الخلاصة وجد أن النماذج (MC-ANN) أعطت نتائج أفضل قليلا من تلك (ANN) غير المدمجة مع (MC) في حين وجدت أنها مناسبة في منع التنبؤ بقيم هطول سالبة غير مادية ، وذلك بالحفاظ على النسبة المئوية للأشهر الجافة.

1 Introduction

Agricultural and socio-economical activities, and increasing human and environmental demands are all strongly connected to the planning and management of water resources. Precipitation, as one driven factor of water, has always been important. It has been so in arid and semi-arid regions particularly; as, in such regions, surface water courses either do not exist or they are generally intermittent or ephemeral, thus making groundwater storage the unique water income fed by precipitation, the unique source of water. As a result of this fact, analysis of precipitation is important in dry regions.

As a complex natural process, precipitation is variable both in time and space. It is observed and recorded on a network of meteorological stations each representing one point on the earth surface. A well-distributed observation network

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of stations is required to distribute point-scale precipitation to area-scale. The spatial distribution does not necessarily be homogeneous although stations might cover all around study area, and their heterogeneous scatter might result in significant differences than results obtained through their individual use [1–3].

Studies devoted to the analysis of precipitation data in the arid Middle East (Jordan in particular) are rare. Variability in the precipitation data of Jordan was analyzed by Shehadeh [4] and recently by Freiwan and Kadioglu [5], its periodicity by Tarawneh and Kadioglu [6], and the structural characteristics by Dahamsheh and Aksoy [7] and Freiwan and Kadioglu [8]. For modeling purposes, Freiwan and Cigizoglu [9], Dahamsheh and Aksoy [10], and Aksoy and Dahamsheh [11] worked for forecasting precipitation in Jordan using the data-driven technique, artificial neural network (ANN). Freiwan and Cigizoglu [9] used the feed-forward back-propagation (FFBP) artificial neural networks (ANNs) to predict monthly precipitation in the Amman meteorological station; and Dahamsheh and Aksoy [10] developed FFBP ANN models for Amman, Baqura, and Safawi. In addition to the FFBP model, Aksoy and Dahamsheh [11] developed radial basis function (RBF) and generalized regression (GR) ANNs for the three meteorological stations named above together with the multiple linear regression (MLR). Two more particular examples of using ANN in arid environments are given by Han and Felker [12] and Yang et al. [13], the former applied the method for estimation of daily soil evaporation from average relative air humidity, air temperature, wind speed and soil water content in a cactus field in Texas, USA while the latter used the same technique for the prediction of groundwater levels in the arid and semi-arid regions of Western Jilin province of China.

In this study, based on their well-established foundation of modeling hydrometeorological processes as summarized above, ANNs are used for the purpose of forecasting 1-month ahead precipitation in an arid region. This study improves ANN models of Aksoy and Dahamsheh [11] by incorporating Markov Chains (MCs) into the ANN models. This is an innovative way to remove the physically meaningless negative forecasts.

Following sections of this study introduce first data used. The models are then explained after which results are presented. Finally, conclusions are listed together with possible future studies.

2 Study Area and Data Analysis

Jordan is a country in the semi-arid to arid climatic region in the Middle East that suffers from water scarcity and its uneven distribution. More than 90 % of the country receives an annual total precipitation less than 200 mm on average, and the amount of water that evaporates back to the atmosphere exceeds 90 % of precipitation. Important basins such as Azraq supplying Jordanian major cities with drinking water started to suffer from depletion of groundwater levels, and became completely dry due to the fact that the total water demand in the country is as almost twice as the conventional water supply that includes the safe yield of all available groundwater and surface water resources [14].

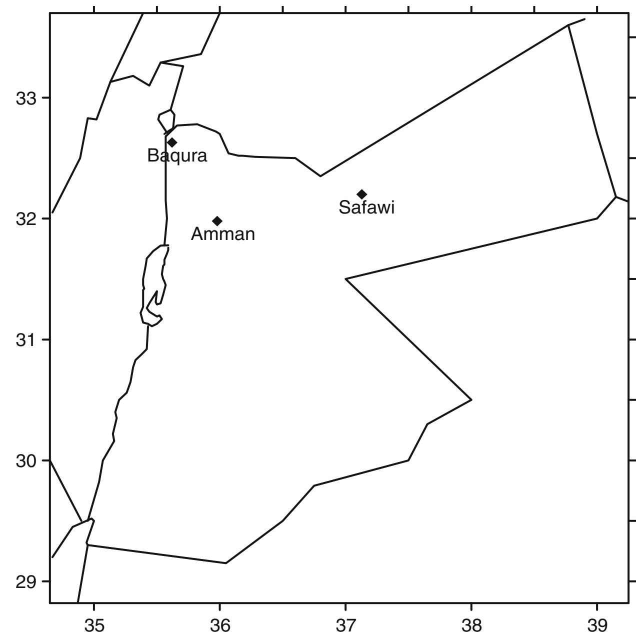

Fig. 1 The location of the Baqura, Amman, and Safawi meteorological stations in Jordan

Three meteorological stations of Jordan Meteorological Department were selected in this study as used by Aksoy and Dahamsheh [11]. Stations are seen in Fig. 1 together with their statistical characteristics given in Table 1 from which it is seen that precipitation is the highest in Baqura and lowest in Safawi due to their locations in the mountain and desert regions, respectively. When variability is concerned, the desert station intends to be more variable than the other two stations. Frequency distributions of the recorded precipitation are far from being normal and the interdependency between the subsequent years has a negative correlation. A detailed analysis of structural characteristics of the data can be found in Dahamsheh and Aksoy [10] who concluded that precipitation in Jordan was skewed and obeyed non-normal distributions.

3 ANN Models and MC Incorporation

The methods like ANN type models have been enormously applied in different disciplines since more than a decade [15–20]. In this study, the impact of MC incorporation into

Table 1 Characteristics of Baqura, Amman, and Safawi meteorological stations and statistics calculated from the annual total precipitation data

Station	Observation period	Latitude N	Longitude E	Elevation (m)	Mean (mm)	Standard deviation (mm)	Median (mm)	C_v	C_s	r_1	Maximum (mm)	Year maximum observed	Minimum (mm)	Year minimum observed
Baqura	1968–2005	32.63	35.62	−170	397.6	125.9	377.0	0.32	1.13	−0.110	822.7	1992	168.2	1999
Amman	1923–2005	31.98	35.98	772	270.4	90.0	263.3	0.33	0.30	−0.133	476.5	1938	98.0	1995
Safawi	1943–2005	32.20	37.13	672	71.9	39.3	64.7	0.55	1.37	−0.083	213.5	1988	7.5	1958

Latitudes and longitudes are provided in degrees. C_v Coefficient of variation, C_s Skewness coefficient, r_1 Lag-one autocorrelation coefficient

the ANN-based data-driven models has been assessed for monthly precipitation forecast. Three ANN models, namely, FFBP, RBF, and GR ANNs, were established. Various architectures were tried to reach the desired architecture to give the best forecasting performance. The ANN models have already been well documented in literature (e.g., [21]); therefore here, they are only briefed from Aksoy and Dahamsheh [11].

3.1 Feed-Forward Back-Propagation ANN

The FFBP ANN consists of three or more layers, namely, input layer, hidden layer(s) and output layer, each with a certain number of neurons. The number of input (independent) variables directly gives the number of neurons in the input layer. Similarly, the number of dependent variables is equal to the number of neurons in the output layer. The number of neurons in the hidden layer is subject to determination by a trial-and-error procedure with which the error between the observed variable and the model output is minimized. Using a proper activation function f, the input variables (x_i, $i = 1, \ldots, n$) are processed in the hidden layer as:

$$z_j = f\left(\sum_{i=1}^{n} x_i w_{ij} + b_j\right), \quad j = 1, \ldots, h \tag{1}$$

where w_{ij} is the weight of the connection from the ith input neuron to the jth hidden neuron, and b_j is the bias for the jth hidden neuron. The activation function in the hidden layer is given by

$$\log sig(n) = \frac{1}{\left[1 + \exp(-n)\right]} \tag{2}$$

where n is the free variable. In this study, the network has only one hidden layer. It is noted, from Eq. (1), that h neurons exist in the hidden layer. In order to obtain the model output, the outputs of the hidden layer (z_j, $j = 1, \ldots, h$) are transformed by

$$y_k = f\left(\sum_{j=1}^{h} z_j w_{jk} + b_k\right), \quad k = 1, \ldots, m \tag{3}$$

where w_{jk} is the weight of the connection from the jth hidden neuron to the kth output neuron, and b_k is the bias for the kth output neuron. The same activation function as in the hidden layer [Eq. (2)] was used in the output layer. It is noted, from Eq. (3), that m neurons exist in the output layer. The activation function [Eq. (2)] requires that the data are normalized. Therefore, data were normalized to range between 0 and 1 using

$$x_n = \frac{x_0 - x_{min}}{x_{max} - x_{min}} \tag{4}$$

where x_n and x_0 represent the normalized and original training data, and x_{min} and x_{max} correspond to the minimum and maximum values among the training data.

3.2 Radial Basis Function ANN

The RBF ANN consists of three layers, namely, input, pattern and output layers. In the pattern layer, a RBF is fixed to transform the input vector ($\mathbf{x}$) in a non-linear fashion on a new vector as

$$z_j = \phi(\mathbf{x}), \ j = 1, \ldots, h \tag{5}$$

and to produce the output of the model by

$$y_k = \sum_{j=1}^{h} z_j w_{jk} + b_k, k = 1, \ldots, m \tag{6}$$

3.3 Generalized Regression ANN

The GR ANN consists of four layers: input, pattern, summation, and output. The input layer is made of input vectors. Each unit in the input layer is connected to the pattern layer. The summation layer has two neurons called S-summation and D-summation. The final layer covers the output vector obtained for each input vector $\mathbf{x}^i$, $i = 1, \ldots, p$, where p is the number of elements in the training patterns. The output is then given by

$$y_i(x) = \frac{\sum_{i=1}^{p} w_i \exp\left[-D(x, x_i)\right]}{\sum_{i=1}^{p} \exp\left[-D(x, x_i)\right]} \tag{7}$$

where w_i is the weight of the connection between the ith unit in the pattern layer and the S-summation neuron. D is a function (also known as Gaussian D function) used to pass the input layer units to the pattern layer.

3.4 Markov Chain-Incorporated ANN Models

In this study, MCs were incorporated into the existing ANN models of Aksoy and Dahamsheh [11] with the aim to improve their ability in forecasting number of months with and without precipitation. The models are denoted as MC-ANN and called MC-incorporated ANN models. In the MC-ANN models, as shown in Fig. 2, it is first determined if a particular month is wet or dry using MC. A 1/0 MC can be used for forecasting the state of the month (wet or dry), where '1' stands for the occurrence of precipitation (wet month) and '0' for the non-occurrence (dry month). When MC forecasts that the month has no precipitation, the model skips the ANN part of the model and returns back to the next month to determine its state (wet or dry).

Markov chains are based on the transition probabilities matrix, which, for a two-state MC, can be given as

$$p_{i,j} = \begin{bmatrix} p_{11} & p_{10} \\ p_{01} & p_{00} \end{bmatrix} \tag{8}$$

where p_{ij} shows probability of transition from a month with state i to a month with state j. If n_{ij} is the total number of months of observation in state j with the previous state i,

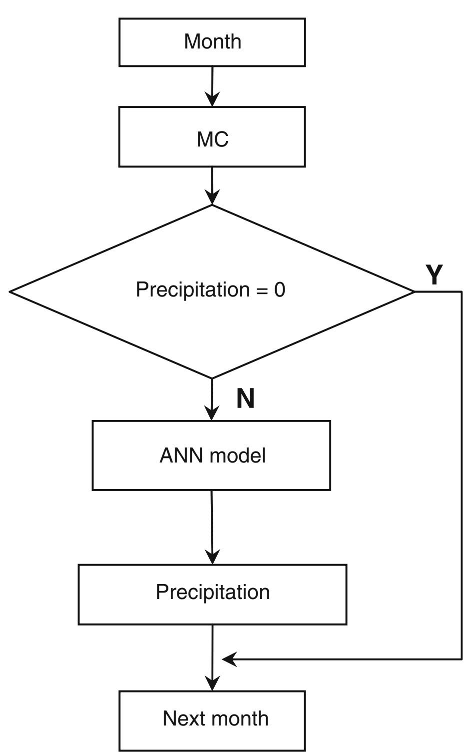

Fig. 2 Flowchart of MC-ANN model

probability of transition from state i to state j can be calculated as

$$p_{ij} = \frac{n_{ij}}{\sum_j n_{ij}}; \; i, j = 0, \; 1 \tag{9}$$

The probabilities are determined for each month of the year due to seasonal effects. The sum of each row in the matrix (Eq. 8) equals one:

$$\sum_j p_{ij} = 1 \tag{10}$$

Thus, the number of parameters required is two, resulting in 24 parameters in total at monthly basis.

4 Model Calibration (Training)

The MC-ANN models were applied on the monthly total precipitation of the three meteorological stations: Baqura, Amman, and Safawi. Monthly data of the first 28, 73, and 53 years (i.e., 336, 876, and 636 months) of each station were used to calibrate the models. For the three stations, the last 10 years (120 months) covering the common period of 1996–2005 were used for validation.

Calibration of MCs covers determination of transition probabilities using the calibration data set. Presented in Table 2 are transition probabilities calculated from the monthly total precipitation of each station. Dash given in September for Amman should be interpreted that this particular month has never been wet during the calibration period. Similarly, the period from January to March has never been dry. The same interpretation is valid for other stations.

In the calibration stage of ANN models, appropriate input vector, number of neurons, type of activation functions, spread coefficients (when applicable), etc. were decided to construct the ANN model. In this study, different combinations of the antecedent precipitation and a periodic component were used to construct the appropriate input vector of the forecasting model by minimizing the mean square error (MSE) calculated for each case from the observed and forecasted precipitation as:

$$\mathrm{MSE} = \frac{\sum_{i=1}^{N} (P_{\mathrm{o},i} - P_{\mathrm{f},i})^2}{N} \tag{11}$$

where $P_{\mathrm{f},i}$ and $P_{\mathrm{o},i}$ show, respectively, the forecasted and observed total precipitation in month i, which goes up to the total number of months N. The determination coefficient (R^2), as an additional measure to quantify the linear relationship between the observed and forecasted precipitation is maximized as

Table 2 Transition probabilities of the 1/0 MC

Month	Baqura		Amman		Safawi	
	p_{11}	p_{00}	p_{11}	p_{00}	p_{11}	p_{00}
January	1.000	–	1.000	–	0.960	0.000
February	1.000	–	1.000	–	0.961	0.000
March	1.000	–	0.986	–	0.902	0.000
April	0.929	–	0.931	0.000	0.688	0.200
May	0.462	0.500	0.647	0.600	0.595	0.750
June	0.154	1.000	0.065	0.963	0.000	0.963
July	0.000	1.000	0.000	0.986	0.000	1.000
August	–	1.000	0.000	1.000	–	1.000
September	–	0.893	–	0.918	–	0.943
October	1.000	0.160	0.667	0.239	0.667	0.540
November	0.958	0.000	0.964	0.056	0.840	0.179
December	1.000	0.000	1.000	0.000	0.932	0.000

$$R^2 = \left[\frac{\sum_{i=1}^{N} (P_{o,\iota} - \bar{P}_o)(P_{f,i} - \bar{P}_f)}{\sqrt{\sum_{i=1}^{N} (P_{o,i} - P_o)^2} \sqrt{\sum_{i=1}^{N} (P_{f,i} - P_f)^2}} \right]^2 \quad (12)$$

The periodic component is calculated as

$$Per(t) = \sin\left(\frac{2\pi\ t}{12}\right) + \cos\left(\frac{2\pi\ t}{12}\right) \quad (13)$$

where t is the number assigned to months starting from January as $t = 1$ to December as $t = 12$.

Among combinations of input vectors investigated for the FFBP ANN model, the best performance was achieved when P_{t-1}, P_{t-2}, P_{t-12}, and $Per(t)$ are used as the input vector. Here P corresponds precipitation, Per is the periodicity as defined in Eq. (13), and t the number assigned to months again as above. It might be important to note that the previous year's precipitation [P_{t-12}] is included in the input vector. Note also that the periodic component [Per] was also used. This shows the importance of the periodicity in the precipitation process in the study area.

After a trial-and-error procedure, number of neurons in the hidden layer to connect the inputs with the outputs was decided as 7 for Baqura and Amman, and 5 for Safawi. As the activation function between the hidden and output layers, the sigmoid function was used. The model inputs and the output were scaled appropriately to fall within the function limit (zero to one). The FFBP ANN was trained by using the Levenberg–Marquardt training algorithm. After the training was over, the weights were used to test the network performance on the test data. The ANN models were trained for 25 epochs. Jordan weather can be classified as arid or semi-arid climate, and most of rainfall in Jordan fall in the 4-month period from December to March, the rest of the year is dry. For this reason, rainfall data in this study consists of a huge amount of zero values (dry months). In order to adapt and regulate zero values, and to improve generalization capabilities of the ANN models, early stopping method is used in the ANN training, and therefore, the ANN models were trained for only 25 epochs.

The adaptive scalar that controls the learning process was set to 0.001. On the other hand, another trial-and-error procedure resulted in an RBF ANN with 26, 38, and 37 neurons in the pattern layer for Baqura, Amman, and Safawi, respectively. The final RBF ANN models were then 4-26-1 for Baqura, 4-38-1 for Amman, and 4-37-1 for Safawi. The spread parameter was taken 5 again by the trail-and-error procedure. Similarly, the GR ANN structure became 4-x-1 for the three stations, in which the spread parameter for the selected stations was found to be equal to 0.06. For both RBF and GR ANNs, the Gaussian activation function was used for pattern layers and the linear function for output layers. The model input and output were scaled appropriately to fall within the function limit (zero to one).

Table 3 shows the performance measures of the calibration stage of the models for the three stations. Additional performance measures other than MSE and R^2 were adopted: MAE (mean absolute error given as the average of the absolute values of the errors); and a and b (the slope and the intercept) in the best-fit linear line of the scatter diagram between the observed and the forecasted precipitation. It was seen that the FFBP ANN model was slightly better calibrated. Also noted was that wetter the region, better the calibration was.

5 Model Validation (Testing)

In Table 4, results obtained from the validation of the models were presented and compared by the same performance measures used in the calibration stage. FFBP seemed to be

Table 3 Performance measures for the calibration period

Station	Baqura			Amman			Safawi		
Model	MC-FFBP	MC-RBF	MC-GR	MC-FFBP	MC-RBF	MC-GR	MC-FFBP	MC-RBF	MC-GR
R^2	0.71	0.60	0.65	0.54	0.49	0.53	0.42	0.32	0.38
MSE (mm^2)	714.5	971.7	881.1	614.6	685.1	633.0	70.0	82.8	76.8
MAE (mm)	15.0	20.2	17.0	14.3	15.4	14.7	5.0	5.3	5.3
A	0.71	0.60	0.57	0.54	0.49	0.47	0.43	0.32	0.31
B	8.6	13.0	13.0	10.0	12.0	11.0	3.5	4.2	3.9

Table 4 Performance measures for the validation period

Station	Baqura			Amman			Safawi		
Model	MC-FFBP	MC-RB	MC-GR	MC-FFBP	MC-RBF	MC-GR	MC-FFBP	MC-RBF	MC-GR
R^2	0.51	0.45	0.23	0.58	0.57	0.25	0.30	0.30	0.24
MSE (mm^2)	1,128.5	1,243.9	1,831.9	380.8	380.9	726.3	54.2	54.2	62.3
MAE (mm)	20.1	20.7	23.3	11.6	11.6	15.4	4.0	4.1	4.3
A	0.57	0.51	0.32	0.66	0.62	0.38	0.31	0.35	0.34
B	12.0	17.0	16.0	9.1	9.9	10.0	2.9	3.1	2.9

better than the other models for Baqura, while RBF performed as good as FFBP for Amman and Safawi.

Results were drawn in Figs. 3, 4, and 5 for the Amman station only, in a more detailed way using additional graphical performance measures explained as follows: The 10-year (120 month) time series of the observed and the forecasted monthly total precipitation were presented [(a) in Figs. 3, 4, 5] together with the scatter diagram of the observed and the forecasted precipitation [(b) in Figs. 3, 4, 5]. In the popular ANN literature, these two graphs are commonly used for comparison. The time series [(a) in Figs. 3, 4, 5] simply compares the observed and the forecasted monthly total precipitation. The scatter diagram [(b) in Figs. 3, 4, 5] shows how the observed versus the forecasted precipitation scatter around the 1:1 perfect line together with the best-fit linear line of the forecast. The fitted linear equation was given above the scatter diagram.

For understanding how well the proposed model performs throughout the validation period, the residual time series [(c) in Figs. 3, 4, 5] was obtained. Here, the residual is defined as the difference between the forecasted and the observed monthly total precipitation given by

$$R = P_{\mathrm{f}} - P_{\mathrm{o}} \tag{14}$$

Monthly mean residuals were plotted [(d) in Figs. 3, 4, 5] to know in which month the model performs well. For this purpose, both the absolute and the relative errors were calculated. Absolute value of the error is important to show the fluctuation of the forecasted values from their observed counterparts. The relative error is required to see if the model under- or over-estimates. For comparable results, the dimensionless version of the residual was calculated [(e) in Figs. 3, 4, 5] by dividing the mean residual by the mean value of the total precipitation of each month. In months with zero total precipitation, the dimensionless residual was not calculated.

Analysis of Figs. 3, 4, and 5 shows that the MC-FFBP and MC-RBF ANN models are as well as each other replicating the observed precipitation time series and clearly better than the MC-GR ANN model. The MC-FFBP is slightly better than the MC-RBF. An argument to support this statement is that the slope of the best fit line is closer to one, and the intercept is closer to zero in case of FFBP model in Fig. 3 than the RBF in Fig. 4. In addition, maximum values were relatively better captured by FFBP than RBF. It is noted that highest maxima were generated by the GR model, but in an inappropriate time.

Similar results were obtained for the Baqura station while results for the other station, Safawi, were not satisfactory. This is important to note that the performance of the ANN models becomes worse with the aridity of the region studied; e.g., forecasts for the Safawi station is the worst due to its location in the desert region of the country.

Also compared are the mean, standard deviation, maximum, and minimum values of the forecasted monthly total precipitation as well as annual total precipitation. These statistics were also calculated at the seasonal scale and com-

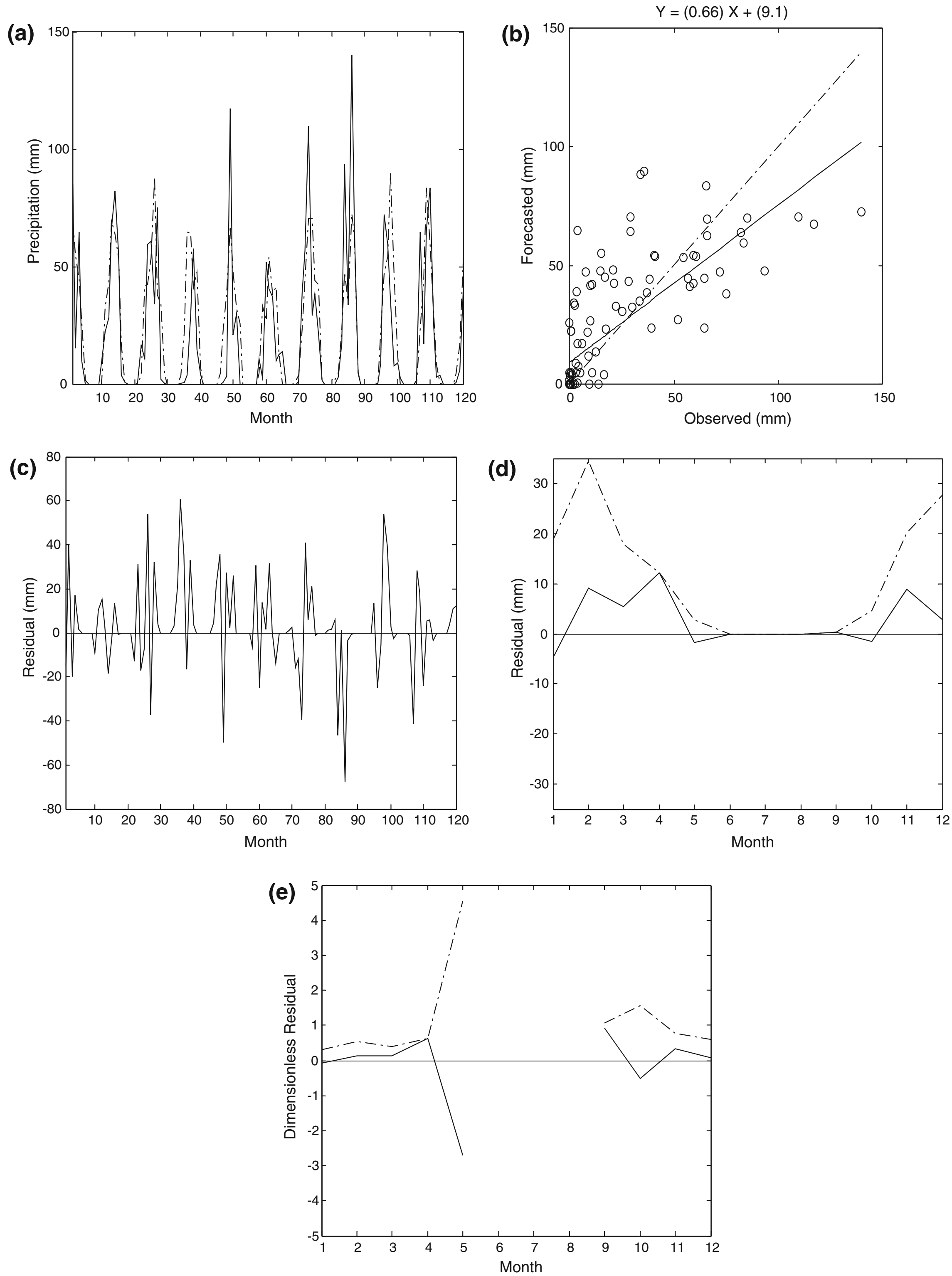

Fig. 3 Results using the MC-FFBP ANN model for the validation data set of Amman station, **a** the forecasted (*dashed*) and observed (*solid*) time series, **b** the scatter diagram between the forecasted and observed precipitation, **c** the residual time series between the forecasted and observed monthly total precipitation, **d** mean absolute error (*dashed*) and mean relative error (*solid*) between the forecasted and observed monthly total precipitation, **e** dimensionless mean absolute error (*dashed*) and mean relative error (*solid*) between the forecasted and observed monthly total precipitation

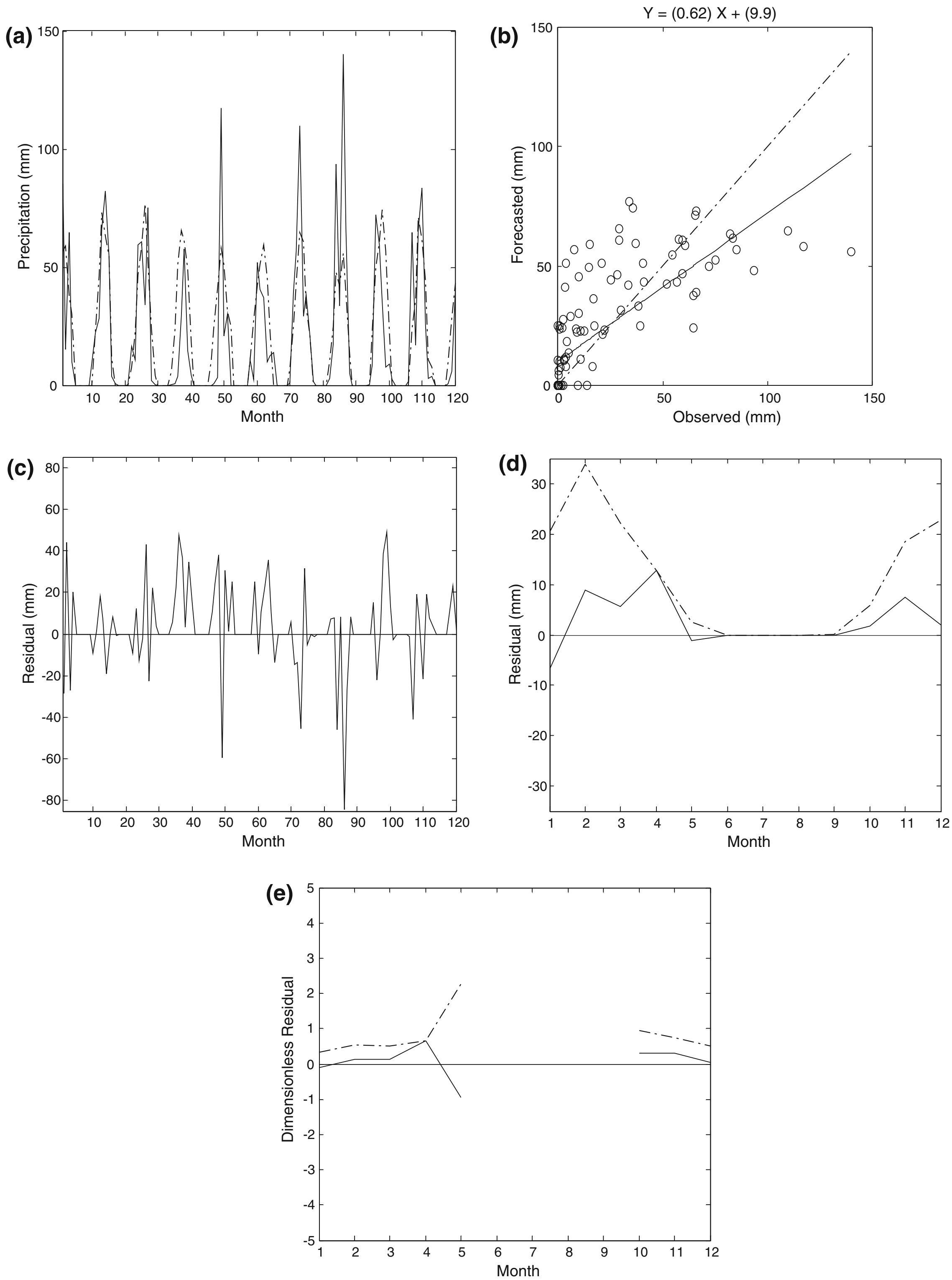

Fig. 4 Results using the MC-RBF ANN model for the validation data set of Amman station (explanation of sub-figures as in Fig. 3)

pared to their observed counterparts in Table 5. At annual scale, the mean annual total precipitation is best modeled by RBF for Baqura and Safawi stations and by GR for Amman. The worst forecasts with respect to preservation of the mean value were obtained by GR for Baqura, RBF for Amman, and FFBP for Safawi. This is such a result that does not allow one to conclude on the best performed model.

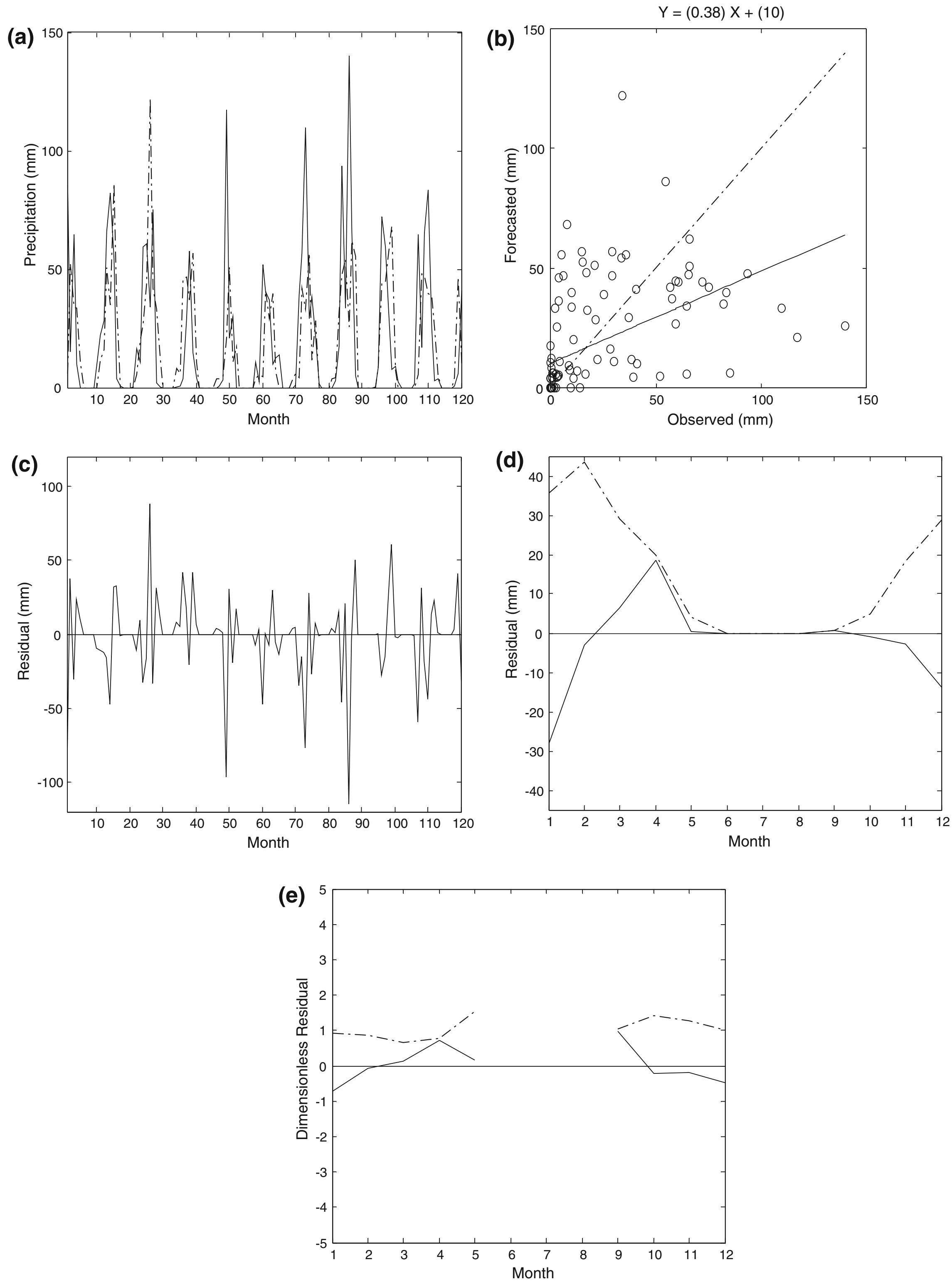

Fig. 5 Results using the MC-GR ANN model for the validation data set of Amman station (explanation of sub-figures as in Fig. 3)

Comparing the mean values of each season in Table 5 shows that RBF performed well in winter and FFBP in spring. In autumn, GR performed better in wet stations (Baqura and Amman), while RBF was better in Safawi, the dry region station. In summer, all models performed perfectly forecasting no precipitation at all.

Table 5 Annual, seasonal, and monthly analysis of observed and forecasted precipitation

	Baqura				Amman				Safawi			
	Obs	MC-FFBP	MC-RBF	MC-GR	Obs	MC-FFBP	MC-RBF	MC-GR	Obs	MC-FFBP	MC-RBF	MC-GR
Annual												
Mean (mm)	385.6	359.4	401.1	317.8	232.5	263.3	263.6	210.0	65.4	55.5	60.0	56.7
SD (mm)	97.9	62.9	38.7	41.7	66.0	31.4	20.7	58.0	27.1	7.9	12.0	11.9
Max (mm)	512.4	454.0	456.9	410.0	325.6	308.0	296.5	313.3	103.0	64.2	71.9	71.4
Min (mm)	168.2	284.8	350.1	267.2	109.4	220.4	223.1	113.7	32.9	43.8	36.7	32.6
DJF												
Mean (mm)	255.4	213.6	226.7	157.4	161.7	165.0	163.1	117.2	38.9	31.4	33.6	32.0
SD (mm)	99.4	45.4	42.6	29.1	47.4	25.9	21.9	40.0	14.1	7.1	10.3	13.6
Max (mm)	491.5	308.3	329.4	203.9	267.5	191.2	185.0	192.8	55.9	45.5	46.9	48.5
Min (mm)	120.8	158.8	162.2	113.5	90.7	119.8	115.9	58.3	9.0	20.6	14.2	10.0
MAM												
Mean (mm)	79.9	83.8	103.1	113.9	47.8	63.8	65.3	73.1	14.1	14.5	15.8	15.7
SD (mm)	45.5	37.2	33.2	61.8	23.1	13.4	9.4	30.8	11.5	3.6	3.8	5.4
Max (mm)	137.7	114.9	167.9	249.6	77.2	86.5	80.2	122.6	39.3	19.6	20.4	22.6
Min (mm)	10.5	0.0	62.0	45.8	18.7	39.4	52.3	28.3	1.2	8.8	10.4	7.2
JJA												
Mean (mm)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
SD (mm)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Max(mm)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Min (mm)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
SON												
Mean (mm)	45.2	54.9	63.6	42.2	21.6	29.2	30.9	18.7	13.8	8.5	9.3	8.5
SD (mm)	42.9	10.0	12.3	29.8	20.5	7.7	6.0	15.3	15.0	3.6	4.8	4.3
Max (mm)	154.6	66.6	82.8	117.0	66.1	45.8	38.9	50.8	45.1	13.1	15.6	13.7
Min (mm)	0.4	37.7	46.4	11.4	0.5	21.1	23.2	5.5	0.0	4.1	0.0	2.2
Monthly												
Mean (mm)	32.1	29.9	33.4	26.5	19.4	21.9	22.0	17.5	5.5	4.6	5.0	4.7
SD(mm)	47.5	37.8	35.7	31.5	29.7	25.8	24.3	22.9	8.8	5.0	5.7	6.1
Max (mm)	243.8	165.3	184.0	187.9	140.1	89.7	77.0	122.2	45.0	21.6	20.6	33.6
Min(mm)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

DJF December–February, *MAM* March–May, *JJA* June–August, *SON* September–November

At monthly scale, FFBP was the best and GR was the worst in Baqura and Amman. In Safawi, it was the opposite case; e.g., FFBP was the worst and GR was the best.

When the ANN models were used without MC incorporated [11], physically meaningless precipitation was forecasted. Forecasting of dry months by means of MCs has been the main focus in this study. This is considered an important improvement to the presented models.

Table 6 shows how well the number of dry months was generated. In ANN models without MCs incorporated, there were no months forecasted without precipitation. Negative precipitations generated in the previous study [11] were all in summer season which has been replaced by zero precipitation after using MCs in the model structure. In addition, two criteria (MSE and R^2) were provided to roughly compare the models with and without MCs. It is seen that the improvement in that sense is not considerable; however, it is considerably important that the negative forecasts were completely eliminated.

The ANN-based forecasting models established for arid region precipitation are not satisfactory in approaching the maxima observed in the time series. This has been the main drawback of previous models developed by Freiwan and Cigizoglu [5], Dahamsheh and Aksoy [10], and Aksoy and Dahamsheh [11]. Forecasts of Freiwan and Cigizoglu [5] were strictly limited to a threshold that was much lower than the

Table 6 Performance of models in forecasting number of dry and wet months, and comparison to ANN models with and without MC incorporated

Station	Model	MSE (mm^2)	R^2	Dry months (%)	
				Observed	Forecasted
Baqura	FFBP	1,102.7	0.51	37	0
	MC-FFBP	1,128.5	0.51	37	51
	RBF	1,246.6	0.45	37	0
	MC-RBF	1,313.3	0.42	37	43
	GR	2,129.7	0.17	37	0
	MC-GR	2,105.0	0.18	37	38
Amman	FFBP	379.9	0.58	38	0
	MC-FFBP	380.9	0.58	38	40
	RBF	383.1	0.57	38	0
	MC-RBF	381.0	0.57	38	43
	GR	1,096.3	0.12	38	0
	MC-GR	1,094.3	0.13	38	40
Safawi	FFBP	55.3	0.28	45	0
	MC-FFBP	54.3	0.30	45	47
	RBF	52.2	0.32	45	0
	MC-RBF	54.2	0.30	45	48
	GR	97.2	0.09	45	0
	MC-GR	94.5	0.12	45	44

observed maximum, thus maximum precipitations were considerably underestimated. Dahamsheh and Aksoy [10] were also not successful in approaching the maxima although slightly better results were obtained. This problem has been given an important and particular attention by Aksoy and Dahamsheh [11] in the development of the model architecture such that higher maxima can be obtained, but results were still not perfect. As a continuation of the mentioned effort, this study as well cannot be considered fully successful in that sense. Still, improvements are needed to forecast the maxima as high as observed maxima.

Based on all these findings, finally, it should be emphasized that none of the models are found to be outstanding in forecasting the observed monthly total precipitation although results were considerably improved compared to the results in Freiwan and Cigizoglu [5]. The main improvement in this study is the removal of negative forecasts although they were rare in number and small in quantity when ANN and MLR models were used without MC incorporated.

Artificial neural networks are data-based models for which huge amount of data is required for their calibration (training). As it was the case in this study, in reality, existing data are usually much less than needed. Therefore, data extension by data generation techniques might be helpful in some cases [22]. Extension of data can further be investigated to possibly improve results of ANN models developed in this study.

6 Conclusions and Further Studies

Based on present results, following conclusions and ideas to further study may be drawn:

1. The ANN models are constructed based on a trial-and-error procedure. Therefore, none of the ANN models in this study turned out to be a best choice, as there may always exist better models to be constructed on the basis of a trial-and-error procedure, with a different architecture, different activation functions or spread coefficients (when applicable).
2. Higher variability of arid region precipitation results in worse performance of ANN models, i.e., increasing variability reduces the success of the models in approaching the observed precipitation sequence. Therefore, intermittent monthly precipitation data of semi-arid to arid regions should be analyzed with more care than perennial precipitation time series of the humid regions.
3. In this study, for each station, monthly precipitation data have been combined together and analyzed as a whole without considering if a month is wet or dry. Clearly, dry months reduce the model efficiency. This limitation of the models can be eliminated and improvements in model performance can be achieved by considering monthly analysis. Monthly models can be proposed at the expense of increase in the model parameters, weights and biases. If a parsimonious model is desired, and if the monthly analysis is therefore found very costly with respect to model parameters, then dry and wet periods in the year can be modeled separately. The observed data can simply be divided into two periods; for instance, above and below the long-term average precipitation to be taken as a threshold. Models can then be constructed separately for each period.
4. If it becomes necessary to analyze the intermittent monthly precipitation record as a whole, then some helping tools should be incorporated into the forecasting models. For instance, MCs among these are used in this study together with ANNs. Good results with forecasting precipitation, particularly in dry months of the year, were obtained and negative precipitations forecasted by ANN models were eliminated.
5. Data required for calibration of ANN models can be generated by means of artificial data generation methods existing in stochastic hydrology. This can further be investigated to possibly eliminate limitations of ANN models.

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