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Precipitation Forecast Using Artificial Neural Networks in Specific Regions of Greece

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Abstract In recent years, significant changes in precipitation regimes have been observed and these manifest in socio economic and ecological problems especially in regions with increased vulnerability such as the Mediterranean region. For this reason, it is necessary to estimate the future projected precipitation on short and long-term basis by analyzing long time series of observed station data. In this study, an effort was made in order to forecast the monthly maximum, minimum, mean and cumulative precipitation totals within a period of the next four consecutive months, using Artificial Neural Networks (ANNs). The precipitation datasets concern monthly totals recorded at four meteorological stations (Alexandroupolis, Thessaloniki, Athens, and Patras), in Greece. For the evaluation of the results and the ability of the developed prognostic models, appropriate statistical indexes such as the coefficient of determination (R^2), the index of agreement (IA) and

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the root mean square error (RMSE) were used. The findings from this analysis showed that the ANN's methodology provides satisfactory precipitation totals in four consecutive months and these results are better results, than those obtained using classical statistical methods. A fairly good consistency between the observed and the predicted precipitation totals at a statistical significance level of $p < 0.01$ for the most of the examined cases has been revealed. More specifically, the Index of Agreement (IA) ranges between 0.523 and 0.867 and the coefficient of determination (R^2) ranges between 0.141 and 0.603. The most accurate forecasts concern the mean monthly and the cumulative precipitation for the next four consecutive months.

Keywords Precipitation forecast · Artificial Neural Networks · Greece

1 Introduction

Global warming, due to the enhanced greenhouse effect, influences precipitation variability and trends. Warming relates to higher water content in the atmosphere (Douville et al. 2002; Trenberth et al. 2003), which results in an increase in the probability of severe convective weather. Anagnostopoulou et al. (2006), studying projected intensity and number of cyclones for the Mediterranean region, observed a future decrease of the frequency of the severe cyclones (<1,000 hPa) at sea level pressure level (SLP), but the future cyclones will be more intense, especially at the 500 hPa level.

Recent studies have concluded that, heavy storms of convective nature in the developed mega-cities could be attributed to the urban heat island (UHI; Nastos and Zerefos 2007, 2008; Paliatsos et al. 2005; Philandras et al. 2010). On the other hand, water scarcity and decreasing run off appear as adverse consequences of climatic change in vulnerable regions such as the Mediterranean region (IPCC 2007). Water scarcity combined with high precipitation intensity is likely to drive in desertification of large areas and therefore change in land use, having as a consequence social–economic impacts.

The majority of the Mediterranean region presents decreasing winter precipitation during the last few decades, mostly starting in the 1970s (Schonwiese et al. 1994; Palutikof et al. 1996; Piervitali et al. 1997; Schonwiese and Rapp 1997). Decreasing precipitation is also evident in large parts of the eastern Mediterranean area (Mantis et al. 1994; Schonwiese et al. 1994). Brunetti et al. (2004), found negative significant trend in the number of wet days all over Italy, and a positive trend in precipitation intensity, which is significant only in the northern regions. Nastos and Zerefos (2009) concluded that the temporal variability of consecutive wet days shows statistically significant (confidence level of 95%) negative trends, mainly in the western region of Greece, characterized by large orographic precipitation amounts (Metaxas et al. 1999). Insignificant positive trends for consecutive dry days appear almost all over the country with emphasis in the southeastern region. The observed decreasing trend in winter and annual precipitation in Greece (Repapis 1986; Nastos 1993; Feidas et al. 2007) is linked mainly to a rising trend in the hemispheric circulation modes of the NAO, which are connected with the Mediterranean Oscillation Index.

The prediction of precipitation is of great importance for agriculture, socio-economic activities and planning/management of water resources in a region. According to the literature several attempts have been carried out in order to forecast precipitation using statistical methods. Juneng et al. (2010) compared the skills of four different forecasting approaches in predicting the one-month lead time of the Malaysian winter season precipitation. The results showed that the appropriate downscaling technique and ensemble of various regional climate models (RCM) forecasts could result in some skill enhancement, particularly over peninsular Malaysia, where other models tend to have lower or no skills. Fernández-Ferrero et al. (2009) compared several statistical downscaling methods for the development of an operational short-term forecast of precipitation in the area of Bilbao (Spain). Results showed that the use of statistical downscaling methods improves the ability of the mesoscale and coarse resolution models to provide quantitative precipitation forecasts. Valverde-Ramirez et al. (2006) developed linear and nonlinear downscaling to establish empirical relationships between the synoptic-scale circulation and observed rainfall over southeastern Brazil. Fox and Wilson (2005) presented an overview of the state of very short period quantitative precipitation forecasting (QPF). What they demonstrated is that there are a number of powerful and practical approaches to the problems of very short-period (QPF), and, as these methods reach maturity, they can be applied in an operational setting.

On the other hand, numerical models have been used successfully for long-term climate prediction (Zwiers and von Storch 2004). In recent years, Artificial Neural Networks (ANNs) have become a desirable model in rainfall–runoff modeling (Nourani et al. 2009), management of floods (Ahmad and Simonovic 2006), surface water level fluctuations (Altunkaynak 2007), ground water level fluctuations (Mohanty et al. 2010) and precipitation forecast (Bodri and Cermak 2000; Sahai et al. 2000; Luck et al. 2000; Silverman and Dracup 2000; Sakellariou and Kambezidis 2004; Cigizoglou and Alp 2004).

Artificial Neural Networks (ANNs) are based on the structure and function of the human brain. Neurons are basic components of the brain. They are essential nerve cells which create a dense network. The first ANNs models were introduced during the decades of 1940 and 1950 with the basic artificial neuron model of McCulloch and Pitts (1943), along with the first ANNs training algorithm of Rosenblatt (1958). In the following decades the use of the ANNs showed significant decline, due to high computing power requirements, which were not available from the computers of that era. The recession was followed by regeneration of ANNs with the introduction of the Hopfield's model (1982, 1987). These are known as Multi-Layer Perceptron (MLP) ANNs, which along with the training algorithm of back-propagation, proposed by Werbos (1974), attract the interest of the scientific community again. Figure 1 shows the architecture of a MLP artificial neural network as well as the training algorithm of back-propagation. The first layer is the input layer with one or more neurons, depending on the number of necessary input data for the proper training of ANN. One or more hidden layers follow with a number of artificial neurons that are necessary for the processing of the input signals. Each neuron of the hidden layer communicates with all the neurons of the next hidden layer, if any, having in each connection a typical weight factor (Fig. 1). Finally, the signal reaches the output layer, where the output value from the ANNs compares with the target value and the error is estimated. Thus, the values of the weight factors are appropriately improved and the training cycle is repeated until the error is acceptable, depending on the application.

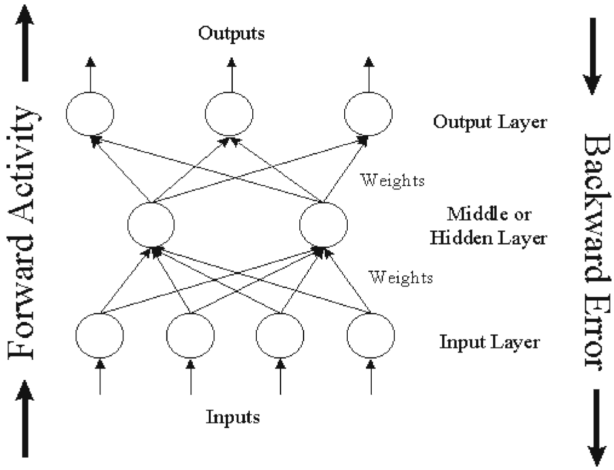

Fig. 1 Typical artificial neural network architecture (Caudill and Butler 1992)

In general, ANNs models can be applied in many different scientific topics such as air pollution levels, bioclimatological parameters, water quality, precipitation prediction, and climate analysis (Melas et al. 2000; Papanastasiou et al. 2007; Freiwan and Cigizoglu 2005; Zwick and Canarelli 1996; Moustris et al. 2009).

The goal of this study is to examine the possibility of long term precipitation forecast (four consecutive months) by the application of ANNs, using long monthly precipitation time series of four meteorological stations in Greece. This research aims to evaluate the ANNs capacity to predict precipitation totals within much longer time with better results than other researchers have done and not to prove that ANNs can predict precipitation better than other classical statistical methods, a subject that has been carried out by many researchers.

2 Data and Methodology

2.1 Case Study and Area

In this study, the monthly precipitation totals recorded at National Observatory of Athens (NOA) for a 115-year period (1891–2005) were used. This time series of NOA is the longest available record of monthly precipitation totals in Greece. Monthly precipitation totals recorded in three meteorological stations of the Hellenic National Meteorological Service (HNMS), with long datasets of monthly precipitation totals (Alexandroupolis 1947–2003; Thessaloniki 1931–2003 and Patras 1901–1993), were also used in the analysis. The list of the stations used, together with their geographical coordinates and altitude above the mean sea level, are presented in Table 1, while the network distribution is shown in Fig. 2.

The short-cut Bartlett test of homogeneity of variance was applied on annual precipitation totals of all the examined time series. This test is performed by dividing

Table 1 Bartlett test (short-cut). Results for precipitation in the considered stations

ID	Station	Longitude	Latitude	Altitude (m)	Period	S^2_{max}/S^2_{min}
1	Athens	23° 58′E	37° 58′N	107	1891–2005	3.187
2	Alexandroupolis	25° 53′E	40° 51′N	3	1947–2003	1.579
3	Mikra	22° 58′E	40° 31′N	5	1931–2003	1.091
4	Patras	21° 44′E	38° 15′N	30	1901–1993	1.237

the time series into k equal sub-periods, where k ≥ 2. In each of these sub-periods, the sample variance S_k^2 for k sub-period was calculated using the following formula:

$$S_k^2 = \frac{1}{n}\left[\sum_{i=1}^{n} x_i^2 - \frac{1}{n}\left(\sum_{i=1}^{n} x_i\right)^2\right]$$

From the values of S_k^2, the largest, denoted by S^2_{max}, and the smallest, denoted by S^2_{min}, were selected. The homogeneity of the examined time series was confirmed by comparing the ratio (Table 1, last column) with the theoretical values at 0.05 significance level (Mitchell et al. 1966). Concerning the four examined stations,

Fig. 2 Map of Greece with the four examined sites

Athens has exhibited the greatest precipitation homogeneity due to its unchanged position since 1891.

In the process, for each month of the year a periodic component (PC) was given according to the mean monthly precipitation total (Table 2; Freiwan and Cigizoglu 2005). More specifically, for each station, the mean monthly precipitation during the examined period was calculated (Table 2, columns 2–5). After that, the mean monthly values of the four stations were averaged (Table 2, column 6) and based on these averages, four classes were extracted corresponding in four particular PC values; that is, PC = 0 for 11.0–22.2 mm, PC = 1 for 24.5–37.2 mm, PC = 2 for 48.0–55.5 mm and PC = 3 for 65.0–84.1 mm (Table 2, column 7).

PC is a constant number for each month of the year and in other words represents the seasonality of precipitation (Freiwan and Cigizoglu 2005). PC seems to be a very important input data for the appropriate training of the constructed ANNs. This conclusion is based upon repeated trials, which were made. Specifically, a large number of different ANNs were constructed and trained. The results showed that the ANNs using PC gave much better results than all the others constructed ANNs.

Figure 3 illustrates the PC value for each month of the year, compared to the mean monthly precipitation totals of the examined time series.

2.2 Precipitation Prediction-Artificial Neural Networks Methodology

In this work, 16 ANNs (ANN#1–ANN#16) were constructed in order to predict the maximum, the minimum, the mean and the cumulative precipitation totals for the next four consecutive months. The first four (ANN#1–ANN#4) for NOA station, the following four (ANN#5–ANN#8) for Patras' station and the last two sets (ANN#9–ANN#12) and (ANN#13–ANN#16) for Mikra and Alexandroupolis, respectively. The sixteen ANNs have one input layer with seven artificial neurons (processing elements), one hidden layer with five artificial neurons and the output layer with one artificial neuron, which basically is the target-predicted value. Generally, there is not a rule-algorithm for the calculation of the optimal number of hidden layers as well

Table 2 Values of mean monthly precipitation amount (mm) and values for the monthly periodic component (PC), for the four examined cities

	Athens (NOA)	Patras	Thessaloniki (MIKRA)	Alexandroupolis	Mean monthly precipitation amount (mm)	PC
January	54.5	104.2	38.5	62.7	65.0	3
February	41.4	84.1	34.1	52.3	53.0	2
March	37.5	67.7	37.9	48.9	48.0	2
April	24.3	49.5	38.6	36.2	37.2	1
May	19.7	28.3	45.0	33.7	31.7	1
June	12.1	15.3	32.4	29.0	22.2	0
July	6.1	3.5	26.6	20.0	14.1	0
August	6.6	4.6	19.5	13.3	11.0	0
September	16.2	24.9	29.4	27.3	24.5	1
October	44.4	83.3	45.4	48.7	55.5	2
November	61.3	112.8	54.1	79.9	77.0	3
December	70.6	129.5	51.8	84.4	84.1	3

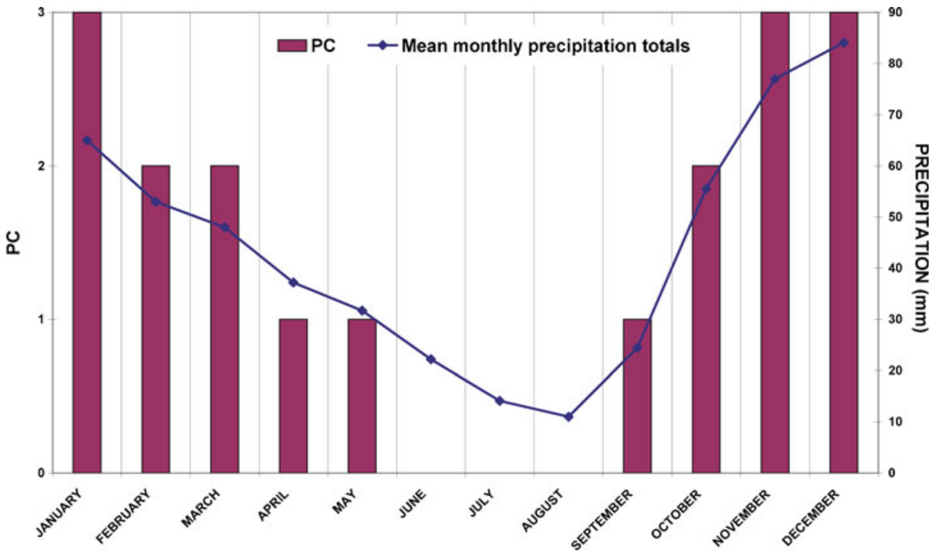

Fig. 3 Periodic component and mean monthly precipitation totals (mm)

as the optimal number of artificial neurons in each hidden layer. Literature indicates that the more limited the number of hidden layers and artificial neurons, the more reliable the model is. Thus, numerous ANNs with a different number of hidden layers and artificial neurons were trained every time and were tested until they reached the best prognosis outcome.

Precipitation data, concerning a specific time period for each meteorological station, were used in the training of the sixteen ANNs. To evaluate the potential of precipitation prediction by the trained ANNs, a different period was used than the one used for the training for each station. For every station's time series, approximately the datasets of the last decade were excluded and the rest of the time series were used as training datasets, while the datasets of the last decade were used as validation datasets. Specifically, for NOA station, the monthly precipitation totals for the period 1891–1989 were used as training datasets, while the monthly precipitation totals for the period 1990–2006 as cross validation datasets, for evaluating the potential of the prediction. For Alexandroupolis station, the monthly precipitation totals for the period 1947–1993 were used as training datasets, while the monthly precipitation totals for the period 1994–2004 as a cross validation datasets. For Patras station, the monthly precipitation totals for the period 1901–1979 were used as training datasets, while the monthly precipitation totals of the period 1980–1992 as a cross validation datasets. For Thessaloniki (Mikra) station, the monthly precipitation totals for the period 1931–1993 were used as training datasets, and the monthly precipitation totals for the period 1994–2004 as cross validation data sets. Table 3 presents the input data, which were necessary for the training of the sixteen constructed ANNs, as well as the results extracted by ANNs. Finally, the dataset giving the best prognosis was chosen.

The cumulative PC of the four previous months was the sum of the PC monthly values (Table 2) of these months. Similarly, the cumulative PC of the four next months was the sum of the PC monthly values of these months. For example, in the

Table 3 Necessary input data for the appropriate ANNs training and the predicted outputs

Inputs	Outputs
Maximum monthly precipitation totals of the four previous months	Maximum monthly precipitation totals of the four next months
Minimum monthly precipitation totals of the four previous months	Minimum monthly precipitation totals of the four next months
Mean monthly precipitation totals of the four previous months	Mean monthly precipitation totals of the four next months
Standard deviation of the mean monthly precipitation totals of the four previous months	Cumulative precipitation totals of the four next months
Cumulative precipitation totals of the four previous months	
Cumulative PC of the four previous months	
Cumulative PC of the four next months	

case of the precipitation prediction for the period January–April, the cumulative PC for these four months was 8 ($3 + 2 + 2 + 1 = 8$), while the cumulative PC of the four previous months (September–December) was 9 ($1 + 2 + 3 + 3 = 9$).

2.3 Evaluation of Predicted Results

The reliability of the predictive model was demonstrated by the use of some statistical indices. In order to establish the credibility and generally the capacity of a good prognosis by the trained ANNs, the Root Mean Square Error (RMSE), the coefficient of determination (R^2) and the Index of Agreement (IA) were used as statistical indices (Willmott 1982; Willmott et al. 1985; Comrie 1997; Walker et al. 1999; Kolehmainen et al. 2001).

The RMSE is a commonly used measure of the differences between the predicted values by a predictable model and the real-observed values. The RMSE was used as a single measure that indicates the ability of the model prediction and has the same units as the predicted value. The smaller the numerical value of RMSE was, the closer the real values were to the predicted values by the model.

In statistics, the coefficient of determination is used in cases of statistical models, whose main purpose is the prediction of future outcomes on the basis of other related information. It is the proportion of the variability in a dataset that is accounted for, by the statistical model. It provides a measure of how well future outcomes are likely to be predicted by the model. It takes values between zero and the unit ($0 \leq R^2 \leq 1$). The closer the value is to the unit, the better and more accurate is the prediction.

The Index of Agreement (Willmott et al. 1985) is a dimensionless measure with values between zero and unit ($0 \leq \text{IA} \leq 1$). When $\text{IA} = 0$ there is no agreement between prediction and observation, while $\text{IA} = 1$ denotes a perfect agreement between prediction and observation.

3 Results and Discussion

Table 4 shows the values of the statistical indices of reliability, such as RMSE, R^2 and IA, for the four examined stations and for each particular case of prediction. For a better understanding of the contents of Table 3, each case of precipitation

Table 4 Statistical indexes for the evaluation of the developed rainfall forecasting models

Case of prediction	R^2	IA	RMSE (mm)
Athens			
A	0.371	0.660	45.9
B	0.244	0.635	12.5
C	0.471	0.756	21.3
D	0.472	0.756	85.3
Patras			
A	0.497	0.818	49.5
B	0.459	0.811	17.7
C	0.603	0.867	25.6
D	0.603	0.867	102.5
Alexandroupolis			
A	0.415	0.751	31.1
B	0.251	0.663	14.3
C	0.508	0.812	17.4
D	0.508	0.812	69.8
Thessaloniki (Mikra)			
A	0.240	0.586	26.6
B	0.141	0.523	9.9
C	0.362	0.695	12.4
D	0.362	0.695	49.5

A maximum monthly precipitation prediction, *B* minimum monthly precipitation prediction, *C* mean monthly precipitation prediction, *D* cumulative precipitation prediction

prediction was matched to a letter. Specifically, for the period under examination, letter A stands for the maximum monthly precipitation prediction, letter B stands for the minimum one, while letters C and D stand for the mean and cumulative precipitation prediction, respectively.

The values of the statistical indices (Table 4) showed that, the best forecast resulted from Patras' input datasets while the worst resulted from Thessaloniki's input datasets. R^2 values indicated that there was a good correlation between the recorded and the predicted precipitation totals, for all the forecasting cases at a statistical significance level of $p < 0.01$. The IA values were very close to the unit in all cases. This declares a good prediction and shows how close the forecasted values were to the recorded ones in most of the cases. It is known from the scientific literature (Willmott et al. 1985) that, IA is a relative measure of error and it is limited to the range of 0–1. IA = 0 means no agreement between prediction and observation and IA = 1 means perfect agreement between prediction and observation.

The most accurate forecasts seem to be the average monthly precipitation prediction (C) as well as the cumulative precipitation prediction (D) for the next four consecutive months. The RMSE values of 102.5 mm (case D for the city of Patras) and 85.3 mm (case D for the city of Athens) seem to be high enough, but both cases concern the prediction of cumulative precipitation totals for the four consecutive months and such high values are expected and observed in both cities.

The predicted and the observed time series of the maximum (a), minimum (b), mean (c) and cumulative (d) precipitation totals for the next four consecutive months, for the station of Patras (best prediction) and the station of Thessaloniki (the worst prediction) are depicted in Figs. 4 and 5, where continuous lines represent the predicted precipitation totals and dotted lines represent the corresponding observed ones.

Similar results have been extracted by other researchers. Sahai et al. (2000) used ANNs for the prediction of total precipitation during the summer monsoon period

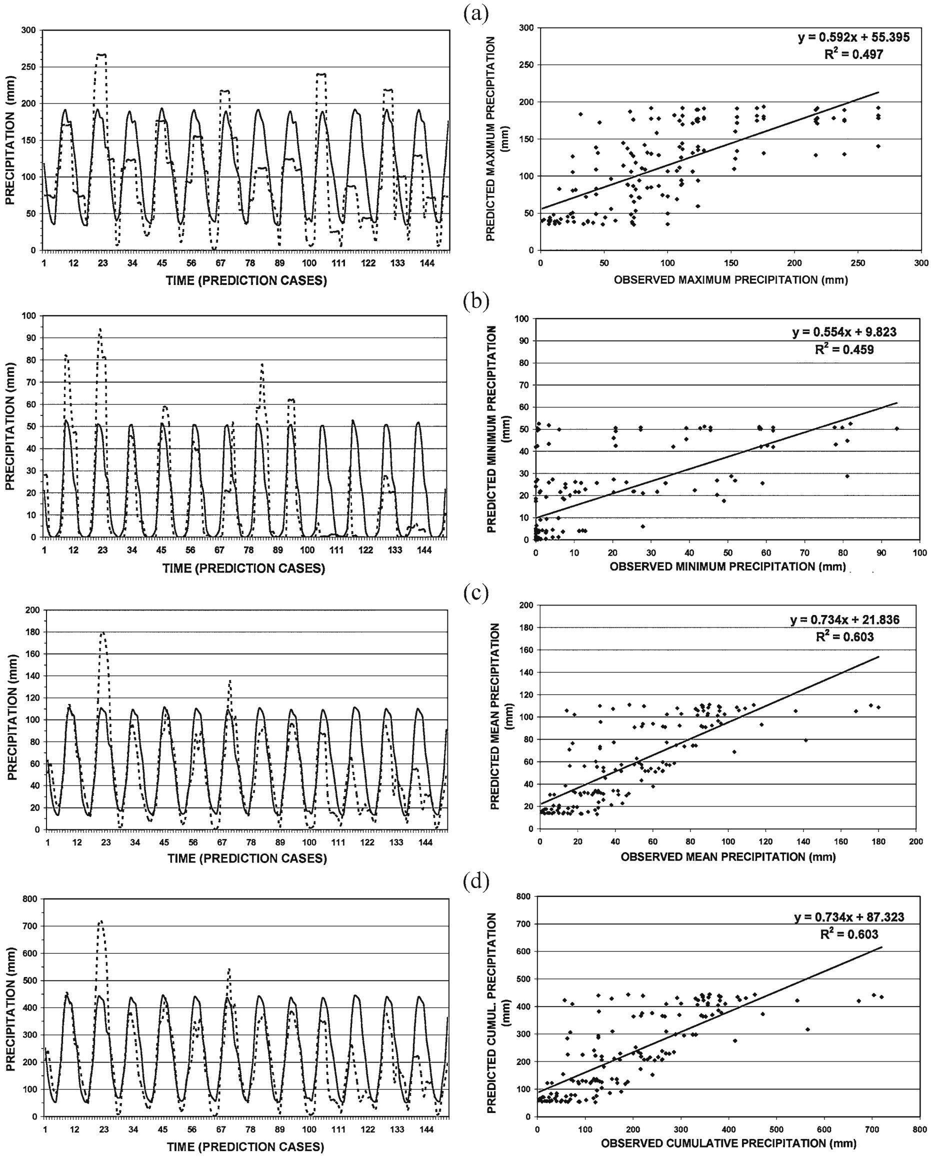

Fig. 4 Prediction of monthly maximum (**a**), minimum (**b**), mean (**c**) and cumulative (**d**) precipitation totals for the next four consecutive months, for the station of Patras, within the period 1980–1992

across India. As input data, precipitation totals from 306 different meteorological stations throughout India during the June, July, August and September months within the period 1871–1994, were used. The ANNs were programmed to give a prediction of the total cumulative precipitation for four consecutive months (June–September) of the current calendar year, based on the input data of the past four years for these four months. The forecasted results were quite satisfactory (Root Mean Square Error, RMSE: 54.2 mm), mainly due to the frequency of occurrence

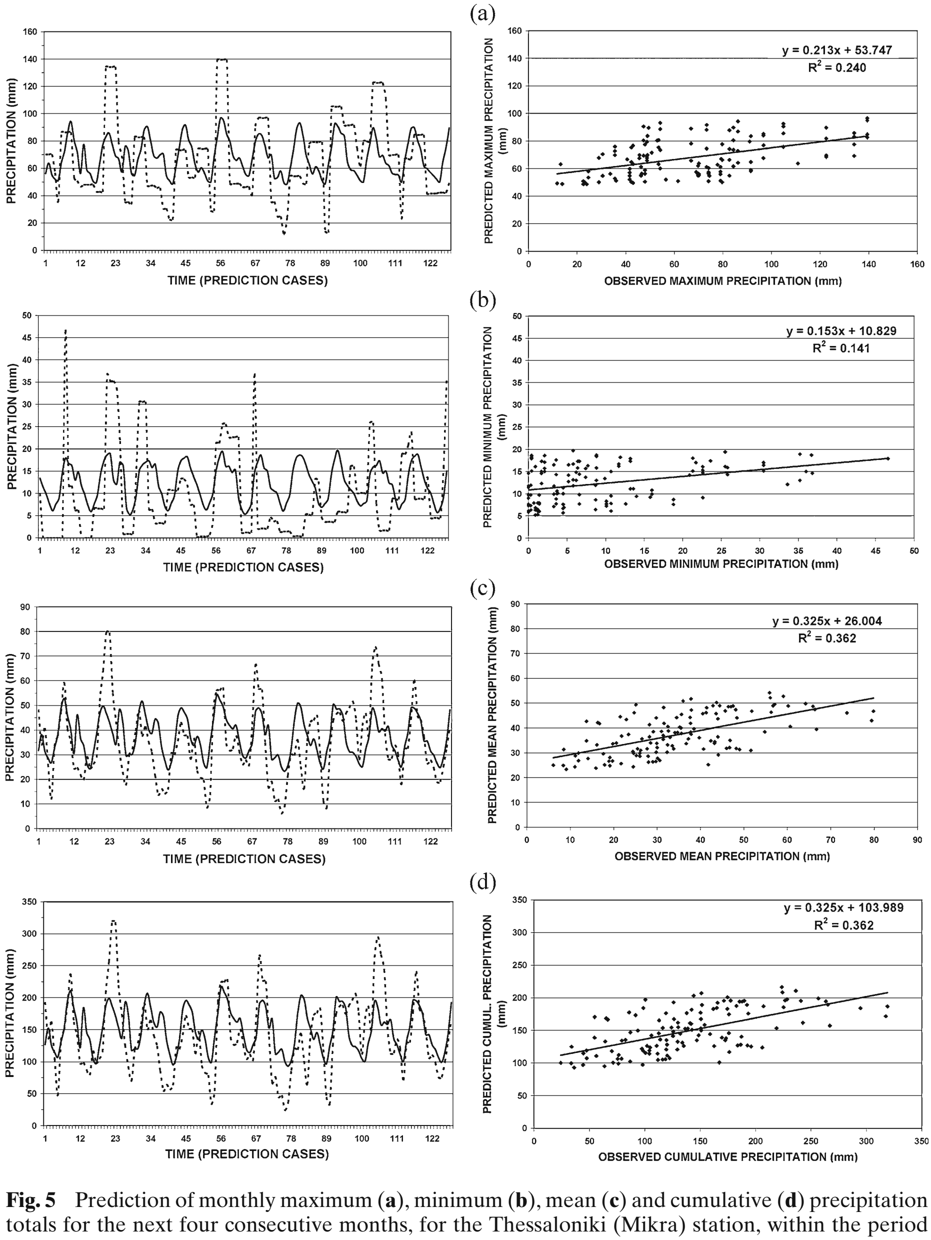

Fig. 5 Prediction of monthly maximum (**a**), minimum (**b**), mean (**c**) and cumulative (**d**) precipitation totals for the next four consecutive months, for the Thessaloniki (Mikra) station, within the period 1994–2004

of heavy precipitation during the summer monsoon in India, as well as the large number of data used for ANNs training. A physical phenomenon appearing high frequency of appearance within time series has impressed a particular experience. The ANNs have the ability to "learn" and get this experience resulting in satisfactory prediction of the phenomenon. Chantasut et al. (2004) developed ANNs in order to predict precipitation using the monthly precipitation values of the period 1941–1999 from 245 different stations along the area of the river Chao Phraya (Thailand). The aim was to predict the precipitation totals for the next month, using as input data the monthly precipitation from each one of the ten previous months. The predicted precipitation totals resulted in RMSE: 0.18 mm. Furthermore, Freiwan and Cigizoglu (2005) developed a number of different Multi-Layer Perceptron (MLP) ANNs, which were trained with the method of back-propagation algorithm in order to predict precipitation for the next month. As input data they used the precipitation totals of the previous two months and a periodic component for each month. The precipitation prediction concerned the area of the airport in Amman, Jordan, during the period 1924–2000. The predicted results were fairly satisfactory in most cases with R^2 between 0.112 and 0.466, and RMSE between 25.8 and 33.6 mm, depending on the ANNs type used in each case. *The predicted results were very satisfactory with a coefficient of determination (R^2) between 0.112 and 0.466, and RMSE between 25.8 and 33.6 mm, depending on the ANNs type used in each case*. Iseri et al. (2005) constructed different types of predictive models, including ANNs, in order to predict the precipitation in the Fukuoka-Japan. Prediction was based on data recorded during the period 1901–1997. Their prediction was based on the August precipitation totals. The change of the sea surface temperature and three different climate indices of the previous three to twelve months before the predicted month were used as input data for ANNs training. Between all the models, ANNs showed the best forecasting ability, with a coefficient of determination between 0.147 and 0.366. Finally, Mar and Naing (2008) used ANNs in order to predict the monthly precipitation totals in Yangon (Myanmar-South East Asia). For this purpose they used, as input data, monthly precipitation totals, covering the period 1970–2006. They developed different set of ANNs with a different number of artificial neurons in each one, and the predicted precipitation totals resulted in RMSE between 9.9 and 22.9 mm, depending on the ANNs type.

A limitation of our study is that, the developed ANNs did not have the ability to forecast the peaks in all cases. This means that in order to predict the peaks, more data are necessary for ANNs' training. It is likely that, the ANNs could not gain the necessary experience for the correct prediction of the peak of the precipitation totals. This is because the extreme precipitation cases occur with low frequency in all stations and in random sequence, in contrast to high frequency of occurrence of heavy precipitation during the summer monsoon in India (Sahai et al. (2000). Greece, located in the Eastern Mediterranean is not characterized by high frequency of extreme precipitation events. Nastos and Zerefos (2008), using wavelet analysis for the time series of the annual number of days (%) with precipitation greater than 30 mm, in Greece, showed that decadal cycles (10 to 16 years), statistically significant (0.05 c.l.), dominate in the western and eastern regions of Greece. Moreover, 2–10 year periods are exhibited all over the country with less or more significance with respect to time. Therefore, if a phenomenon such as extreme precipitation does not occur with high frequency, then it is difficult to be forecasted successfully by ANNs or other statistical methods. Using only precipitation datasets, the performed ANNs showed that they can forecast the maximum (a), minimum (b), mean (c) and cumulative (d) precipitation totals for the next four consecutive months, satisfactorily. This indicates the usefulness of these ANNs compared to the classical methods already available. Furthermore, the methodology developed in this research could be implemented by other researchers interested in predicting future high intensity storms and cyclones in regions with higher frequency (e.g. summer monsoon in India), than that in Greece. However, an adequate training of the ANNs, based on additional meteorological parameters of the middle and upper atmosphere, such as air temperature, relative humidity, wind speed and direction, barometric pressure, and condensation level, is required.

4 Conclusions

The time series of monthly precipitation totals from four meteorological stations in Greece were used, in order to forecast the monthly maximum, minimum, mean and cumulative precipitation totals for the next four consecutive months by the application of ANNs models. The extracted results showed that the predicted mean monthly as well as the cumulative precipitation totals were in very good agreement ($p < 0.01$) with the respective observed ones concerning all four examined sites. On the other hand, the developed ANNs did not have the ability to forecast the peaks in all cases and this is a limitation of the study, which could be removed by using more data for ANNs' training. Further study could result in more efficient ANNs in the case of precipitation forecast for other stations distributed over the Greek region. In general we could say that the ability of ANNs as a precipitation predictive tool seemed to be quite satisfactory. ANNs could be used in forecasting the seasonal and monthly precipitation totals and this is very important for planning and management of the water sufficiency, which is necessary for life, especially in arid and semi-arid areas.

As it has been mentioned before, during the recent years, many relevant scientific studies have been published, concerning the prediction of precipitation totals, but not enough in the long term prognosis i.e. for four consecutive months. More research is needed in order to improve the capacity of ANNs to forecast precipitation within long-term period.

References

Ahmad S, Simonovic SP (2006) An intelligent decision support for management of floods. Water Resour Manage 20:391–410

Altunkaynak A (2007) Forecasting surface water level fluctuations of Lake Van by artificial neural networks. Water Resour Manage 21(2):399–408

Anagnostopoulou Chr, Tolika K, Flocas H, Maheras P (2006) Cyclones in the Mediterranean region: present and future climate scenarios derived from a general circulation model (HadAM3P). Adv Geosci 7:9–14

Bodri L, Cermak V (2000) Prediction of extreme precipitation using a neural network: application to summer flood occurrence in Moravia. Adv Eng Softw 31:211–221

Brunetti M, Maugeri M, Monti F, Nanni T (2004) Changes in daily precipitation frequency and distribution in Italy over the last 120 years. J Geophys Res 109:D05102. doi:10.1029/2003JD004296

Caudill M, Butler C (1992) Understanding neural networks: computer explorations. MIT Press, Cambridge

Chantasut N, Charoenjit C, Tanprasert C (2004) Predictive mining of rainfall predictions using artificial neural networks for Chao Phraya River. In: Proc of the AFITA/WCCA Joint Congress on IT in Agriculture, Bangkok, Thailand, pp 117–122

Cigizoglou HK, Alp M (2004) Rainfall–runoff modelling using three neural network methods. In: Rutkowski L, Siekmann J, Tadeusiewicz R, Zadeh LA (eds) Artificial Intelligence and Soft Computing-ICAISC 2004, LNAI 3070, Springer, Berlin, pp 166–171

Comrie AC (1997) Comparing neural networks and regression models for ozone forecasting. J Air & Waste Manage Assoc 47:653–663

Douville H, Chauvin F, Planton S, Royer JF, Salas-Melia D, Tyteca S (2002) Sensitivity of the hydrological cycle to increasing amounts of greenhouse gases and aerosols. Clim Dyn 20:45–68

Feidas H, Noulopoulou C, Makrogiannis T, Bora-Senta E (2007) Trend analysis of precipitation time series in Greece and their relationship with circulation using surface and satellite data: 1955–2001. Theor Appl Climatol 87:155–177

Fernández-Ferrero A, Sáenz J, Ibarra-Berasteg G, Fernández J (2009) Evaluation of statistical downscaling in short range precipitation forecasting. Atmos Res 94:448–461

Fox NI, Wilson JW (2005) Very short-period quantitative precipitation forecasting. Atmos Sci Lett 6:7–11

Freiwan M, Cigizoglu HK (2005) Prediction of total monthly rainfall in Jordan using feed forward backpropagation method. Fresen Environ Bull 14:142–151

Hopfield JJ (1982) Neural networks and physical systems with emergent collective computational properties. Proc Natl Acad Sci (USA) 79:2554–2558

Hopfield JJ (1987) Learning algorithms and probability distributions in feed-forward and feed-back networks. Proc Natl Acad Sci (USA) 84:8429–8433

IPCC (2007) Summary for policymakers. In: Solomon S, Qin D, Manning M, Chen Z, Marquis M, Averyt KB, Tignor M, Miller HL (eds) Climate Change 2007: the physical science basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge University Press, Cambridge, United Kingdom/New York, NY, USA

Iseri Y, Dandy GC, Maier HR, Kawamura A, Jinno K (2005) Medium term forecasting of rainfall using artificial neural networks. In: Zerger A, Argent RM (eds) MODSIM 2005 International congress on modelling and simulation. Modelling and Simulation Society of Australia and New Zealand, December 2005, Melbourne, Australia, pp 1834–1840

Juneng L, Tangang FT, Kang H, Lee W-J, Seng YK (2010) Statistical downscaling forecasts for winter monsoon precipitation in Malaysia using multimodel output variables. J Climate 23:17–27

Kolehmainen M, Martikainen H, Ruuskanen J (2001) Neural networks and periodic components used in air quality forecasting. Atmos Environ 35:815–825

Luck KC, Ball JE, Sharma A (2000) A study of optimal model lag and spatial inputs to artificial neural networks for rainfall forecasting. J Hydrol 227:56–65

Mantis HT, Repapis CC, Philandras CM, Paliatsos AG, Amanatidis GT (1994) The spatial and temporal structure of the precipitation climate the Eastern Mediterranean; Background for a study of Climate Change. In: A Ghazi, P Mathy, C Zerefos (eds) EUR 17458—Eastern Europe and Global Change, Kassandra, Halkidiki, Greece, October 3–10, 1994, pp 125–131

Mar KW, Naing TT (2008) Optimum neural network architecture for precipitation prediction of Myanmar. World Academy of Science, Engineering and Technology 48:130–134

McCulloch W, Pitts W (1943) A logical calculus of the ideas imminent in nervous activity. Bull Math Biophys 5:33–115

Melas D, Kioutsoukis I, Ziomas I (2000) Neural network model for predicting peak photochemical pollutant levels. J Air & Waste Manage Assoc 50:495–501

Metaxas DA, Philandras CM, Nastos PT, Repapis CC (1999) Variability of precipitation pattern in Greece during the year. Fresen Environ Bull 8:1–6

Mitchell JM, Dzerdzeevsku B, Flohn H, Hofmeyr WL, Lamb HH, Rao KN, Wallen CC (1966) Climatic change, WMO technical note 79. WMO No 195, TP-100, World Meteorological Organization, Geneva, p 79

Mohanty S, Jha MK, Kumar A, Sudheer KP (2010) Artificial neural network modeling for groundwater level forecasting in a River Island of Eastern India. Proceedings of workshop on groundwater scenario and quality in Orissa. Water Resour Manage 24:1845–1865

Moustris K, Ziomas IC, Paliatsos AG (2009) 24 hours in advance forecasting of thermal comfort–discomfort levels during the hot period of the year at representative locations of Athens city, Greece. Fresen Environ Bull 18:601–608

Nastos PT (1993) Changements de la pluviosite en region Hellenique pendant la période 1858–1992. Proceedings of the 6^{th} Colloque International de Climatologie, pp 183–190

Nastos PT, Zerefos CS (2007) On extreme daily precipitation totals at Athens, Greece. Adv Geosci 10:1–8

Nastos PT, Zerefos CS (2008) Decadal changes in extreme daily precipitation in Greece. Adv Geosci 16:55–62

Nastos PT, Zerefos CS (2009) Spatial and temporal variability of consecutive dry and wet days in Greece. Atmos Res 94:616–628
Nourani V, Komasi M, Mano A (2009) A multivariate ANN-wavelet approach for rainfall–runoff modeling. Water Resour Manage 23:2877–2894
Paliatsos AG, Nastos PT, Tzavelas G, Panagiotakos DB (2005) Characteristics of precipitation in Athens area, Greece. Fresen Environ Bull 14:422–428
Palutikof JP, Trigo RM, Adcock ST (1996) Scenarios of future rainfall over the Mediterranean: is the region drying? Proc. Mediterranean Desertification, Research Results and Policy Implications, Crete, Greece, 20 October–1 November 1996
Papanastasiou DK, Melas D, Kioutsioukis I (2007) Development and assessment of neural network and multiple regression models in order to predict PM10 levels in a medium-sized Mediterranean city. Water Air Soil Poll 182:325–334
Philandras CM, Nastos PT, Paliatsos AG, Repapis CC (2010) Study of the rain intensity in Athens and Thessaloniki, Greece. Adv Geosci 23:37–45
Piervitali E, Colasino M, Conte M (1997) Signals of climatic change in the Central–Western Mediterranean basin. Theor Appl Climatol 58:211–219
Repapis CC (1986) Temporal fluctuations of precipitation in Greece. Rivista di Meteor Aeron XLVI(1–2):19–25
Rosenblatt F (1958) The Perceptron: A probabilistic model for information storage and organization in the brain. Psychol Rev 65:386–408
Sahai AK, Soman MK, Satyan V (2000) All India summer monsoon rainfall prediction using an artificial neural network. Clim Dynam 16:291–302
Sakellariou NK, Kambezidis HD (2004) Prediction of the total rainfall amount during August and November in the Athens area, Greece. Fresen Environ Bull 13:289–292
Schonwiese CD, Rapp J (1997) Climate trend atlas on Europe—Based on observations 1891–1890. Dordrecht, The Netherlands
Schonwiese CD, Rapp J, Fuchs T, Denhard M (1994) Observed climate trends in Europe 1891–1990. Meteorol Z NF 38:51–63
Silverman D, Dracup JA (2000) Artificial neural networks and long-range precipitation predictions in California. J Appl Meteorol 39:57–66
Trenberth KE, Dai A, Rasmussen RM, Parsons DB (2003) The changing character of precipitation. Bull Amer Meteorol Soc 84:1205–1217
Valverde-Ramirez MC, Ferreira NJ, Fraga de Campos Velho H (2006) Linear and nonlinear statistical downscaling for rainfall forecasting over southeastern Brazil. Weather Forecast 21:969–989
Walker SE, Slordal LH, Guerreiro C, Gram F, Grønskei KE (1999) Air pollution exposure monitoring and estimation Part II. Model evaluation and population exposure. J Environ Monitor 1:321–326
Werbos P (1974) Beyond regression: new tools for prediction and analysis on the behavior sciences. PhD Thesis, Harvard University
Willmott CJ (1982) Some comments on the evaluation of model performance. Bull Amer Meteorol Soc 63:1309–1313
Willmott CJ, Ackleson SG, Davis RE et al (1985) Statistics for the evaluation and comparison of models. J Geoph Res 90:8995–9005
Zwick A, Canarelli P (1996) Climate sensitivity analysis using neural networks. Fresen Environ Bull 5:700–705
Zwiers FW, von Storch H (2004) On the role of statistics in climate research. Int J Climatol 24:665–680