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ORIGINAL PAPER

Comparative study among different time series models applied to monthly rainfall forecasting in semi-arid climate condition

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Abstract The aim of this study is to investigate the ability of different time series models in forecasting monthly rainfall. In order to do this, monthly rainfall data were collected from 9 rainfall stations in North Khorasan province (North east of Iran) from 1989 to 2012. R software was used to predict the highest rainfall in these 9 rain gage stations for the time period 2002–2012 using monthly highest rainfall data of 1989–2002. In this study, AR, MA, ARMA, ARIMA, and SARIMA with 11 different structures based on trial and error were examined. Because the trend, seasonal and jump components are deterministic components, it is not necessary to model these components, but modeling of random component is very important for rainfall forecasting. So, the main data series was decomposed (for AR, MA and ARMA models) and the random part has been modeled. After that, the random component was collected with the seasonal and trend component and the amount of rainfall was simulated. But for ARIMA and SARIMA, models fitted on original series. The result showed that in 33 % of data MA(2), in 22 % of data AR(1) and

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ARMA(2, 1) and in 11.11 % of data MA(1) and ARIMA(1, 1, 2) had the best performance in monthly rainfall forecasting. On the other hand, best time series model by change of data could vary. So, it is important to assess all the time series models for any area and any hydrological parameter.

Keywords Rainfall forecasting · Time series · AR · MA · ARMA · ARIMA

1 Introduction

Rainfall is the most important part of the hydrology cycle (Venkata Ramana et al. 2013). It is the result of many complex physical processes that induce particular features and make its observation complex (Akrour et al. 2014). The investigation and analysis of precipitation is so essential for prediction of metrological information (Radhakrishnan and Dinesh 2006), and accurate prediction of precipitation is vital to better management of water resources, especially in arid environment (Feng et al. 2015).

In last decades, many techniques have been used as suitable tools for modeling and forecasting the meteorological information such as precipitation (Soltani et al. 2007; Shamshirband et al. 2015). In these techniques, time series modeling is an important technique in simulation, prediction and decision making of hydrology cycle components (Soltani et al. 2007; Delleur et al. 1976; Salas and Fernandez 1993; Hipel and McLeod 1994). A time series is observation of a variable at discrete points of time (usually equal distances) that measured and sorted according to time (Chatfield 2001). This technique is used to explain data using statistical and graphical methods, to select the best statistical models to explain the data generating process, to predict the future amounts of a series and controlling a given process (Radhakrishnan and Dinesh 2006; Brockwell and Davis 1996).

Time series theory carried out by many scientists to address hydrological problems (Bras and Rodriguez-Iturbe 1985; Lin and Lee 1992; Brockwell and Davis 1996). In most cases, finding these hydrological problems due to the high side factors (several natural and anthropogenic factors) is very difficult (Adhikary et al. 2012; Kim et al. 2005). Previous methods, such as regression, exponential smoothing, and auto-regressive integrated moving average are accessible for hydrological time series analysis (Mirzavand and Ghazavi 2015). Building time series models consists of three steps: identification, assessment and error detection (Shirmohammadi et al. 2013). Mirzavand and Ghazavi (2015) compared several time series models such as autoregressive, moving average, autoregressive moving average (ARMA), autoregressive integrated moving average (ARIMA), and seasonal autoregressive integrated moving average (SARIMA) to find the best model for groundwater level fluctuation forecasting. They concluded that combining time series models have positive points in terms of groundwater level fluctuation prediction.

Hydrological time series modeling based on stochastic models has been confirmed by many researcher, because these models are proper choice for the area where nothing but the hydrological time series data is available (Adhikary et al. 2012). Stochastic models such as the Markov, Box-Jenkins (BJ), SARIMA, ARMA, periodic autoregressive (PAR), transfer function noise (TFN) and periodic transfer function noise (PTFN) are in use for these goals (Box et al. 1994; Hipel and Mcleod 1994; Brockwell and Davis 2010; Mirzavand et al. 2014; Mirzavand and Ghazavi 2015). Many applications of these models have been accepted to be very useful technique for rainfall data forecasting over time in several studies (Pebesma et al. 2005; Silva 2006; Radhakrishnan and Dinesh 2006; Soltani et al. 2007; Willems 2009; Mair and Fares 2011; Dutta et al. 2012; Adhikary et al. 2012). The selection of a suitable technique for modeling a phenomenon depends on various factors such as data accuracy, time, cost, ease of use of the model's results, interpretation of results and etc. (Mondal and Wasimi 2007; Adhikary et al. 2012). That is why, determination of the best model among the vary models for prediction is very important. Many researchers used the time series models in simulation and prediction of precipitation but comparison of stochastic time series models such as AR, MA, ARMA, ARIMA, and SARIMA for rainfall predicting was not reported. So, the aim of this study is to assessment of the ability these models for rainfall predicting in semi-arid climate condition.

2 Materials and methods

2.1 Study area

North Khorasan province located in northeast of Iran with geographical longitude: 55°17′–61°15′E, and geographical latitude: 30°24′–38°17′N (Fig. 1). The North Khorasan has an area of 28,434 km^2. The study area has a semi-arid climate condition. The mean annual temperature is about 15 °C and the annual rainfall mainly ranges between 120 and 300 mm, which is mostly concentrated in the winter months. In order to prepare data for modeling, monthly rainfall data were collected from 9 rainfall stations in North Khorasan province (Northeast of Iran) from 1989 to 2012 (Table 1), corrected the statistical defect and then normality test data on the residuals of each fitted model using the Kolmogorov–Smirnov were done (the algorithm of modeling is shown in Fig. 2. The stations used in this study along with some of their characteristics are presented in Table 1.

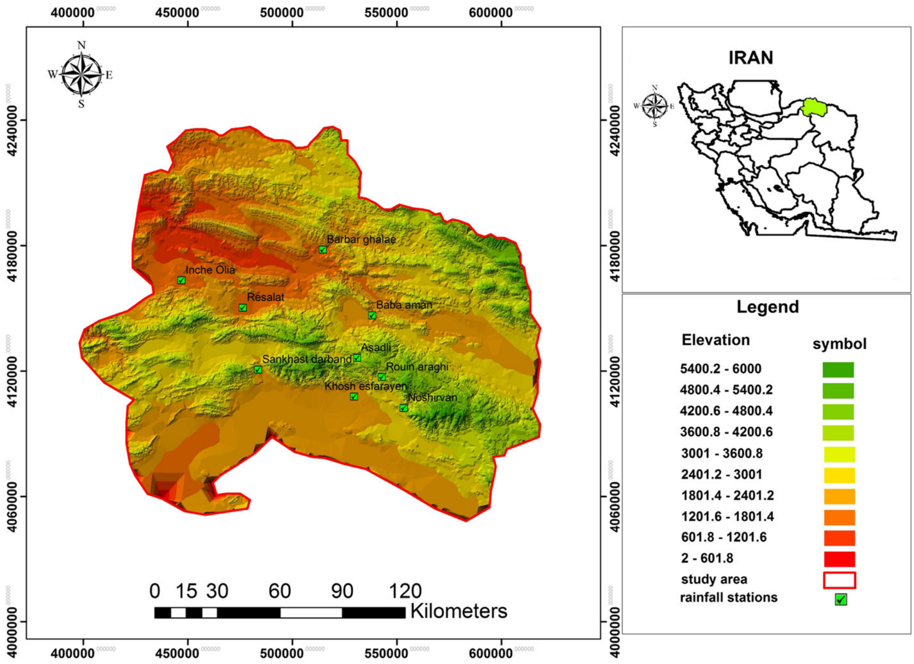

Fig. 1 Spatial location of selected rainfall stations

Table 1 Rainfall stations characteristics

Station	Height (m)	Range of values (mm/year)
Asadli	1800	203–553
IncheOlia	770	142–426
Baba aman	1020	159–488
Barbarghalae	960	134–398
Khoshesfarayen	1200	127–334
Resalat	1200	149–453
Ruin Araghi	1650	132–441
Sankhastdarband	1160	56–415
Noshirvan	1490	157–566

2.2 Time series models

Generally, the models for time series data can have different forms and represent different non-deterministic processes (Sokolnikov 2013; Mirzavand and Ghazavi 2015). Most modeling of time series takes place based on a linear technique. AR, MA and ARMA models have linear base (Klose et al. 2004; Mirzavand and Ghazavi 2015). In this research,

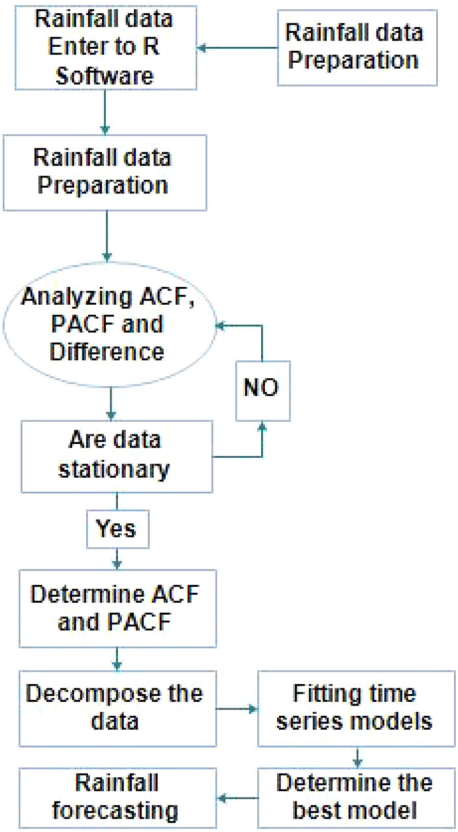

Fig. 2 Algorithm used for rainfall forecasting in this research

AR, MA, ARMA, ARIMA, and SARIMA models on 11 different structures based on trial and error were examined and used to assess the ability of these models in monthly rainfall prediction.

2.2.1 AR model

In a series where persistency is present, that is the event outcome of $(t + 1)$th period is dependent on the present tth period magnitude and those preceding values, then for such a series, the observed sequences X_1, X_2, …, X_t is used to fit an AR model.

Autoregressive model can be expressed as Eq. (1):

$$z_t = \phi_1 z_{t-1} + \phi_2 z_{t-2} + \cdots \phi_p z_{t-p} + a_t, \quad (1)$$

where $\phi 1$, ϕ_2, …, ϕ_p. are model parameters and coefficient and a_t is the random component of the data that follows a normal distribution with mean 0 (Mirzavand and Ghazavi 2015).

2.2.2 MA model

Moving average models are simple covariance stationary and ergodic models that can use for a wide variety of autocorrelation patterns (Mirzavand and Ghazavi 2015).

Moving Average model can be expressed as Eq. (2):

$$z_t = \theta_1 a_{t-1} + \theta_2 a_{t-2} + \ldots \theta_q a_{t-q} + a_t, \quad (2)$$

where θ_1, θ_2, …, θ_q are model parameters and coefficient and a_t is the random component of the data that follows a normal distribution with mean 0 (Hannan 1971; Mirzavand and Ghazavi 2015).

2.2.3 ARMA model

The ARMA model is a synthesis of an AR and a MA model. ARMA model form a type of linear models which are widely applicable and parsimonious in parameterization. ARMA (p, q) model can be expressed as Eq. (3):

$$Z_t = \delta + \sum_{i=1}^{p} \phi_i z_{t-1} + \sum_{j=1}^{q} \varphi_j e_{t-j} + e_t \quad (3)$$

where δ is the stationary part of the ARMA model, φ_i points out the ith autoregressive coefficient, ϕ_j is the jth moving average coefficient, it shows the error part at time period t, and Z_t refers the value of rainfall observed or predicted at time period t (Erdem and Shi. 2011; Behnia and Rezaeian 2015; Mirzavand and Ghazavi 2015).

2.2.4 ARIMA and SARIMA models

Autoregressive integrated moving average (ARIMA) models are one of the well-known linear models for time series modeling and predicting (Mirzavand and Ghazavi 2015). ARIMA models have been originated from the synthesis of AR and MA models. ARIMA is used to model time series data behavior and to make predictions (Shirmohammadi et al. 2013). ARIMA modeling uses correlational methods and could be used to model arrays that may not be observable in plotted data (Box et al. 1994; Mirzavand and Ghazavi 2015).

In ARIMA, the future amount of a parameter is assumed to be a linear function of past observations and random errors (Behnia and Rezaeian 2015). A SARIMA model can be explained as ARIMA (p, d, q) (P, D, Q)s, where (p, d, q) is the non-seasonal component of the model and (P, D, Q)s is the seasonal component of the model in which is the order of non-seasonal autoregression, d is the number of regular differencing, q is the order of non-seasonal Moving Average, P is the order of seasonal autoregression, D is the number of seasonal differencing, Q is the order of seasonal Moving Average, and s is the length of season (Faruk 2010; Mirzavand and Ghazavi 2015).

2.3 Model selection

In most of the carried out researches, in order to determine the best model, partial autocorrelation function (PACF) and autocorrelation function (ACF) have been used (Mirzavand and Ghazavi 2015). But, to improve the model selection accuracy, Akaike information criteria (AIC) and coefficient of determination (R^2) have been used in this research in addition to PACF and ACF (Mirzavand and Ghazavi 2015).

AIC and R^2 can be expressed as Eqs. (4) and (5) (Hu 2007):

$$\mathrm{AIC}(k) = n \ln(\mathrm{MSE}) + 2k \tag{4}$$

$$R^2 = \frac{\left[\sum_{i=1}^{n} (qi - \bar{q})(\hat{qi} - \bar{\hat{q}})\right]^2}{\sum_{i=1}^{n} (qi - \bar{q})^2 \sum_{i=1}^{n} (\hat{qi} - \bar{\hat{q}})^2} \tag{5}$$

where n is the number of data points (which used for calibration), and k is the number of free parameters used in modeling process. MSE stands for mean square error. q_i, $\hat{qi}$, are observed value and the estimated values and $\bar{\hat{q}}$ and $\bar{q}$ are the estimated mean values and computational model outputs, respectively (Mirzavand and Ghazavi 2015).

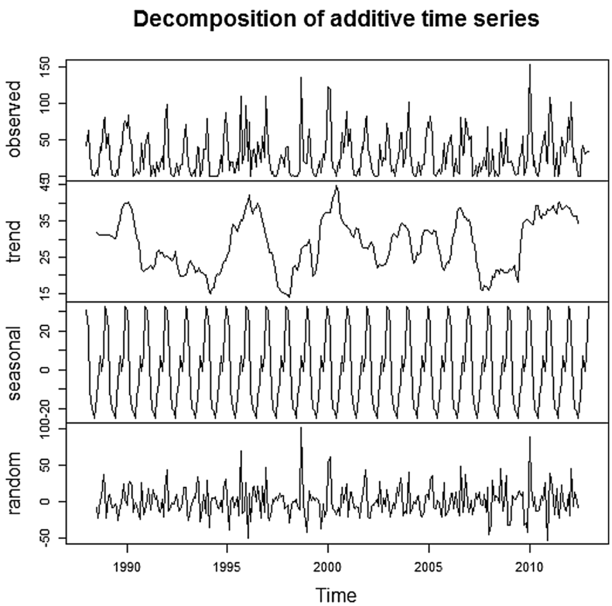

Fig. 3 Time series graphs with random, seasonal and trend components in Asadli station

Table 2 The results of time series models in Asadli, Barbarghalae, Resalat, Noshirvan, Khoshesfarayen

Station models		Asadli			Barbarghalae			Resalat			Noshirvan			Khoshesfarayen		
		Model coefficient	AIC	R^2	Model coefficient	AIC	R^2	Model coefficient	AIC	R^2	Model coefficient	AIC	R^2	Model coefficient	AIC	R^2
AR(1)	ϕ_1	0.3721	2833.48	0.66	0.2839	2568.82	0.51	0.3384	2703.81	0.63	0.4515	2826.75	0.66	0.3735	2689.77	0.69
AR(2)	ϕ_1	0.3805	2835.33	0.65	0.2609	2568.84	0.51	0.3109	2703.9	0.63	0.4349	2828.35	0.66	0.3453	2690.07	0.69
	ϕ_2	−0.0226			0.0811			0.0798			0.0364			0.0749		
MA(1)	θ_1	0.3471	2837.71	0.66	0.2329	2573.75	0.51	0.266	2712.21	0.63	0.3494	2844.13	0.66	0.2971	2700.19	0.69
MA(2)	θ_1	0.3617	2835.68	0.65	0.2451	2567.91	0.51	0.2925	2699.05	0.63	0.4088	2822.39	0.66	0.3235	2688.42	0.69
	θ_2	0.1330			0.1746			0.2542			0.2969			0.2267		
ARMA (1,1)	ϕ_1	0.3339	2835.37	0.65	0.4294	2569.66	0.51	0.4387	2704.87	0.63	0.4842	2828.54	0.66	0.4684	2690.81	0.69
	θ_1	0.0445			−0.1556			−0.1115			−0.0408			−0.1087		
ARMA (1,2)	ϕ_1	0.2195	2836.89	0.65	0.2201	2569.01	0.51	0.1485	2700.36	0.63	0.2273	2822.87	0.66	0.2822	2688.68	0.69
	θ_1	0.1541			0.0375			0.1601			0.2033			0.0585		
	θ_2	0.0723			0.1374			0.2216			0.2275			0.1593		
ARMA (2,1)	ϕ_1	1.2109	2824.58	0.61	0.0805	2570.52	0.51	−0.0238	2704.57	0.63	−0.5358	2826.05	0.66	0.0647	2691.28	0.69
	ϕ_2	−0.4147			0.1366			0.2093			0.4480			0.1902		
	θ_1	−0.8296			0.1804			0.3319			0.9731			0.2785		
ARMA (2,2)	ϕ_1	1.732	2768.24	0.61	1.7348	2537.61	0.41	1.7343	2639.13	0.51	1.7303	2747.88	0.48	1.7321	2623.33	0.47
	ϕ_2	−0.9999			−0.9999			−0.9999			−0.9969			−0.9997		
	θ_1	−1.7260			−1.7300			−1.7294			−1.6786			−1.7227		
	θ_2	0.9916			0.9939			0.9910			0.9322			0.9995		
ARIMA (1,1,2)	ϕ_1	0.3443	2831.74	0.66	0.4389	2567.04	0.41	0.4477	2701.65	0.52	0.4921	2824.6	0.48	0.4771	2687.53	0.47
	d	1			1			1			1			1		
	θ_1	−0.9623			−1.161			−1.1163			−1.0446			−1.1133		
	θ_2	−0.0377			0.1610			0.1163			0.0446			0.1133		

Table 2 continued

Station models		Asadli			Barbarghalae			Resalat			Noshirvan			Khoshesfarayen		
		Model coefficient	AIC	R^2	Model coefficient	AIC	R^2	Model coefficient	AIC	R^2	Model coefficient	AIC	R^2	Model coefficient	AIC	R^2
ARIMA (1,2,1)	ϕ_1	−0.2955	2906.88	0.66	−0.4070	2637.01	0.46	−0.3815	2765.93	0.62	−0.2968	2882.53	0.61	−0.3617	2749.36	0.53
	d	2			2			2			2			2		
	θ_1	−1.0000			−1.0000			−1.0000			−1.0000			−0.9999		
SARIMA (1,1,0) (1,1,1)(12)	ϕ_1	−0.4538	2748.25	0.57	−0.4903	2523.37	0.30	−0.5088	2546.9	0.58	−0.4326	2715.58	0.44	−0.4767	2614.37	0.47
	d	1			1			1			1			1		
	Φ_1	0.1111			0.1343			0.0645			0.1520			−0.0057		
	D	1			1			1			1			1		
	Θ_1	−0.9591			−1.0000			−1.0000			−0.9999			−1.000		
SARIMA (1,1,1) (1,1,1)(12)	ϕ_1	0.0854	2649.84	0.57	0.1451	2451.9	0.43	0.0836	2546.9	0.58	0.1930	2639.02	0.63	0.1309	2536.09	0.62
	d	1			1			1			1			1		
	θ_1	−1.0000			−1.0000			−1.0000			−1.000			−1.0000		
	Φ_2	0.0980			0.0949			0.0497			0.1168			−0.0016		
	D	1			1			1			1			1		
	Θ_2	−0.9661			−0.9997			−0.9765			−0.9401			−1.000		

Table 3 The results of time series models in IncheOlia, Ruin Araghi, Sankhastdarband, Baba aman

Station models	IncheOlia				Ruin Araghi			Sankhastdarband			Baba aman		
	Model coefficient		AIC	R^2	Model coefficient	AIC	R^2	Model coefficient	AIC	R^2	Model coefficient	AIC	R^2
AR(1)	ϕ_1	0.3744	2576.03	0.55	0.3465	2785.38	0.67	0.4035	2670.29	0.65	0.3691	2703.89	0.64
AR(2)	ϕ_1	0.3316	2574.09	0.55	0.3255	2786.29	0.67	0.3768	2671.02	0.65	0.3467	2704.79	0.64
	ϕ_2	0.1143			0.0601			0.0653			0.0605		
MA(1)	θ_1	0.2704	2589.37	0.55	0.2878	2792.81	0.67	0.3214	2682.44	0.65	0.2937	2713.67	0.64
MA(2)	θ_1	0.3215	2565.62	0.55	0.3078	2786.11	0.67	0.3664	2672.08	0.65	0.3239	2702.03	0.64
	θ_2	0.3022			0.1781			0.1918			0.2231		
ARMA (1,1)	ϕ_1	0.490	2576.28	0.55	0.4385	2786.7	0.67	0.4951	2671.41	0.65	0.4433	2705.3	0.64
	θ_1	−0.1307			−0.1037			−0.1086			−0.0849		
ARMA (1,2)	ϕ_1	0.1850	2566.52	0.55	0.2886	2786.65	0.67	0.3756	2671.91	0.65	0.2318	2702.55	0.64
	θ_1	0.1544			0.0323			−0.0004			0.1099		
	θ_2	0.2649			0.1149			0.0934			0.1770		
ARMA (2,1)	ϕ_1	−0.4270	2569.88	0.55	0.1118	2247.93	0.67	−0.3979	2671.84	0.65	−0.0826	2705.57	0.64
	ϕ_2	0.3996			0.1400			0.3704			0.2352		
	θ_1	0.7844			0.2125			0.7847			0.4257		
ARMA (2,2)	ϕ_1	1.7334	2529.73	0.43	1.7325	2716.84	0.52	1.7153	2640.59	0.56	1.7338	2648.94	0.60
	ϕ_2	−0.9993			−0.9997			−0.979			−0.9997		
	θ_1	−1.7232			−1.7181			−1.5738			−1.7314		
	θ_2	0.9794			0.9899			0.8524			0.9902		
ARIMA (1,1,2)	ϕ_1	0.4982	2573.35	0.42	0.4483	2783.19	0.52	0.5048	2668.09	0.56	0.452	2702.01	0.60
	d	1			1			1			1		
	θ_1	−1.1347			−1.1095			−1.1146			−1.0894		
	θ_2	0.1347			0.1095			0.1146			0.0894		

Table 3 continued

Station models		IncheOlia			Ruin Araghi			Sankhastdarband			Baba aman		
		Model coefficient	AIC	R^2	Model coefficient	AIC	R^2	Model coefficient	AIC	R^2	Model coefficient	AIC	R^2
ARIMA (1,2,1)	ϕ_1	−0.3899	2628.85	0.54	−0.3643	2849.6	0.55	−0.3407	2727.9	0.59	−0.3541	2765.82	0.60
	d	2			2			2			2		
	θ_1	−1.0000			−1.0000			−0.9999			−1.0000		
SARIMA (1,1,0) (1,1,1)(12)	ϕ_1	−0.5038	2506.59	0.51	−0.4741	2718.29	0.56	−0.4666	2577.05	0.44	−0.4734	2630.36	0.44
	d	1			1			1			1		
	Φ_1	−0.0089			0.0330			0.1260			0.017		
	D	1			1			1			1		
	Θ_1	−1.0000			−1.0000			−1.000			−0.9469		
SARIMA (1,1,1) (1,1,1)(12)	ϕ_1	0.1613	2447.63	0.52	0.0878	2627.66	0.63	0.2389	2523.62	0.59	0.1445	2553.11	0.59
	d	1			1			1			1		
	θ_1	−0.9835			−1.0000			−0.9721			−1.0000		
	Φ_2	0.0492			0.0385			0.1098			−0.0163		
	D	1			1			1			1		
	Θ_2	−1.0000			−1.0000			−1.0000			−0.9359		

Typically, the desired model gives higher R^2 or the lowest value of AIC (Mirzavand and Ghazavi 2015). The autocorrelation statistics and the corresponding 95 % confidence interval from lag-0 to lag-20 were obtained for the rainfall time series (Fig. 4a, b). For the rainfall data time series, the PACF was shown significant correlation up to lag-2 within the confidence interval and ACF decline exponentially. Behavior of rainfall data in the study area in Fig. 3 shows the data of interest are the three components (trend, seasonal and random) that we used the random component in forecasting in AR, MA and ARMA. But for modeling based on ARIMA and SARIMA, original series were used.

3 Results

The results obtained from time series models in Asadli, IncheOlia, Baba aman, Barbarghalae, Khoshesfarayen, Resalat, Ruin Araghi, Sankhastdarband and Noshirvan are shown in Tables 2 and 3. Also, the models performance in rainfall simulation versus the observed rainfall is shown in Figs. 5, 6, 7, 8, 9, 10, 11, 12 and 13 in Asadli, IncheOlia, Baba aman, Barbarghalae, Khoshesfarayen, Resalat, Ruin Araghi, Sankhastdarband and Noshirvan stations, respectively. These figures show that the models could forecast three components of rainfall data shown in Fig. 3, but the performance of these models is variable.

4 Discussion

Prediction of the highest of rainfall in 9 rain gage stations (2002–2012) based on monthly highest rainfall data (1989–2002) was carried out using R software. Seasonal, trend, jump and random components are four components of time series data (Mirzavand and Ghazavi 2015) (Fig. A.3) because the trend, seasonal and jump components are deterministic components, which are not necessary to be modeled in, but modeling of random components is very important for water resource management using AR, MA and ARMA models (Mirzavand et al. 2014). Hence, the main time series data were decomposed and the random part has been modeled using AR, MA and ARMA models. But for ARIMA and SARIMA, models fitted on original series.

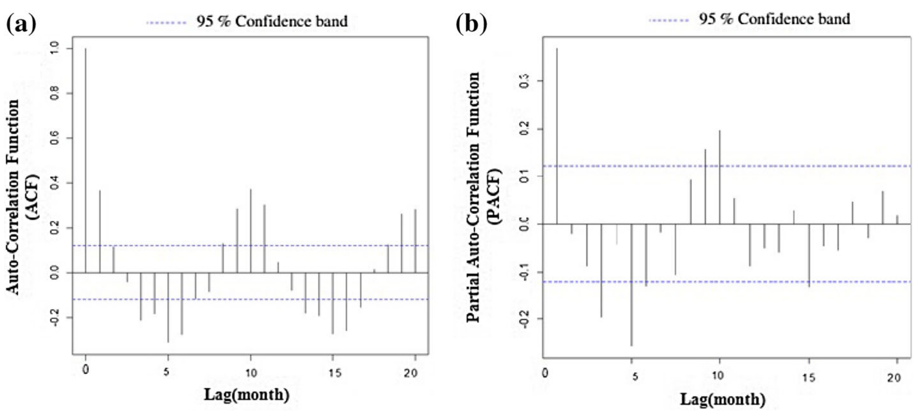

Fig. 4 **a** Autocorrelation and **b** partial autocorrelation functions of the monthly rainfall time series

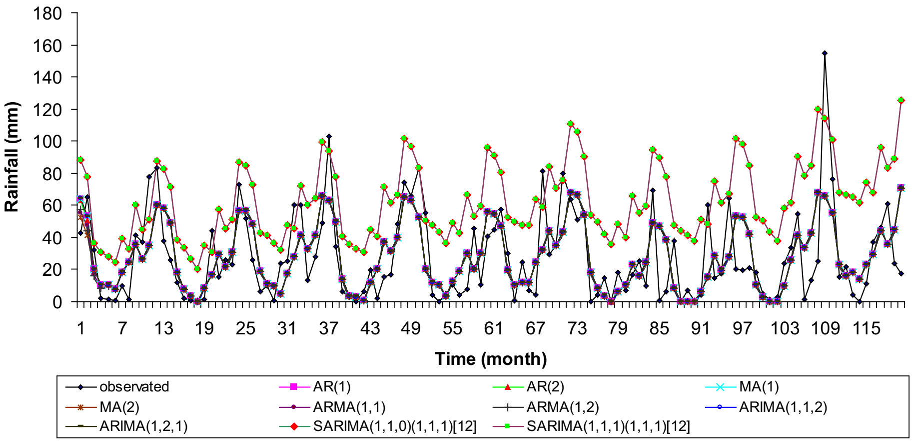

Fig. 5 Models prediction versus observed values in Asadli station

In this study, AR, MA, ARMA, ARIMA and SARIMA models with 11 different structures based on trial and error were examined. With respect to the results, the rainfall data had a seasonal and trend component before the extracting of deterministic components of the time series data (Fig. 3). According to the study carried out by Nirmala and Sundaram (2010), it is possible to determine the best model using ACF and PACF (Fig. 4a, b), but for choice the best model for forecasting, the Akaike criterion and the correlation coefficient were also used for the best model selection. The ACF and PACF of selected time series exposed the seasonal pattern of the monthly rainfall. The results show that in Asadli station ARMA(2, 1) and ARMA(2, 2) and in another stations, ARMA(2, 2) and ARIMA(1, 1, 2) were eliminated. Because the model parameters violated from the absolute value of 1 (Mirzavand et al. 2014) (Tables 2, 3). As results shown, R^2 for these models are less than the other models.

So, the best models which were chosen for highest rainfall prediction in Resalat, IncheOlia and Baba aman was MA(2) and in Khoshesfarayen was MA(1). In Barbarghalae and Sankhastdarband, the best models which was chosen for rainfall prediction were AR(1). Other words, the amount of rainfall at time t is related to random component by the prior amount of rainfall at time t-1 (Mirzavand and Ghazavi 2015). In Asadli station, the best model was ARIMA(1, 1, 2), which it was in line with results that obtained by Kumar Nanda et al. (2013). For Noshirvan and Ruin Araghi, the best model was ARMA(2, 1), which it was in line with results that obtained by Wu et al. (2010). As the results showed for selection of the best model in time series modeling, evaluation of the models according to the AIC and R^2 in addition to using the ACF and PACF graph is necessary. By referring to studies that carried out for rainfall forecasting (Said et al. 2013; Khadar Babu et al. 2011; Kwon et al. 2007; Soltani et al. 2007; Seed et al. 2000), groundwater level forecasting (Mansour et al. 2011; Schaars and Von Asmuth 2012; Poormohammadi et al. 2013; Mirzavand et al. 2014; Mirzavand and Ghazavi 2015) and for river flow prediction (Saeidian and Ebadi 2004; Javidi Sabbaghian and Sharifi 2009), the best model using stochastic models could vary by changing the data. So, it is important to assess all the time series models for any area and any hydrological parameters for choosing the best model for our purpose. Finally, it can be expressed that the stochastic models can be used for the rainfall prediction (Durdu 2010) up to the next 120 months with an acceptable accuracy

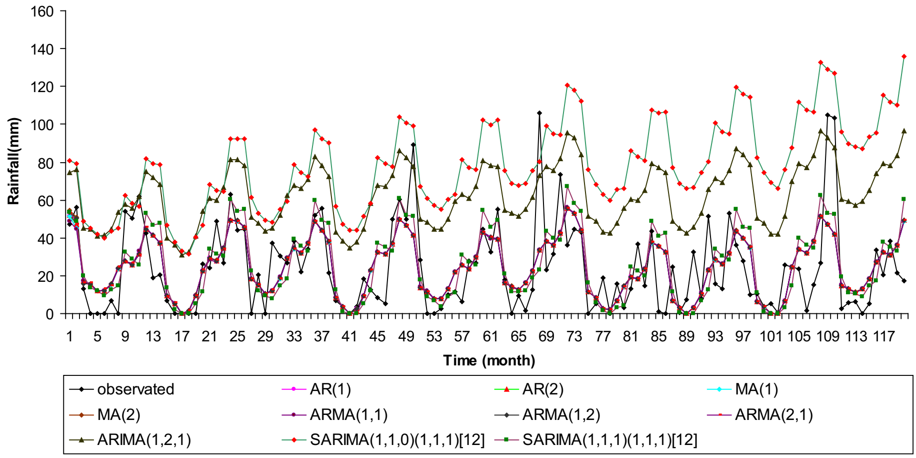

Fig. 6 Models prediction versus observed values in IncheOlia station

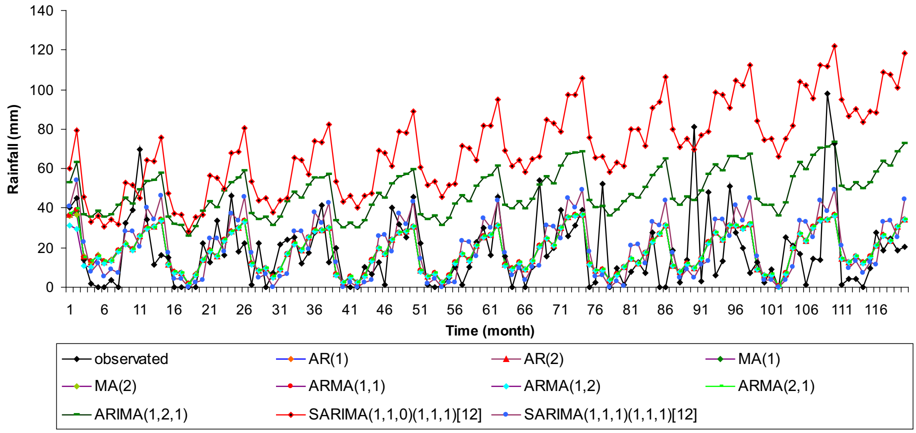

Fig. 7 Models prediction versus observed values in Baba aman station

(presented in Figs. 5, 6, 7, 8, 9, 10, 11, 12, 13). And it is possible that we claim time series models based on the stochastic models is very fast and easy to identify the changes in time series components of rainfall.

5 Conclusions

The result showed that in 33 % of data MA(2), in 22 % of data AR(1) and ARMA(2, 1) and in 11.11 % of data MA(1) and ARIMA(1, 1, 2) were had the best performance in monthly rainfall forecasting. On the other hand, best time series model by change the data could be varied. So, it is important to assess all the time series models for any area and any hydrological parameters to choose the best model for each case. According to the results, in modeling based on time series data, it is important to assess the performance of time series

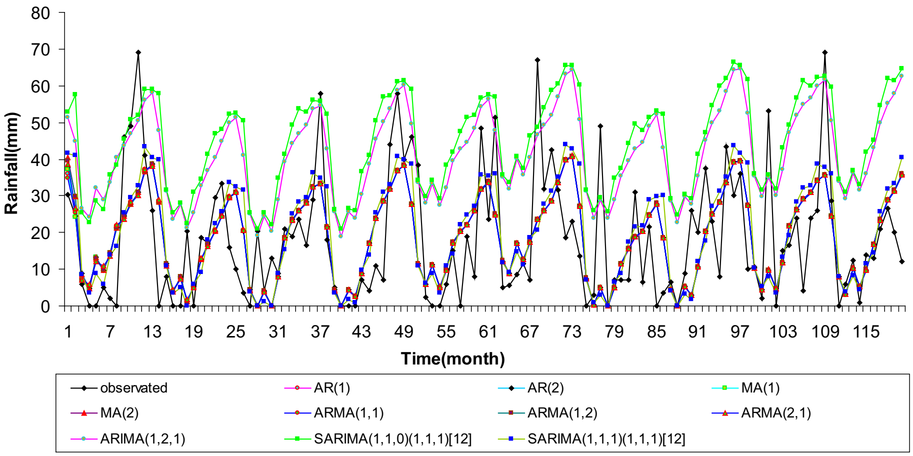

Fig. 8 Models prediction versus observed values in Barbarghalae station

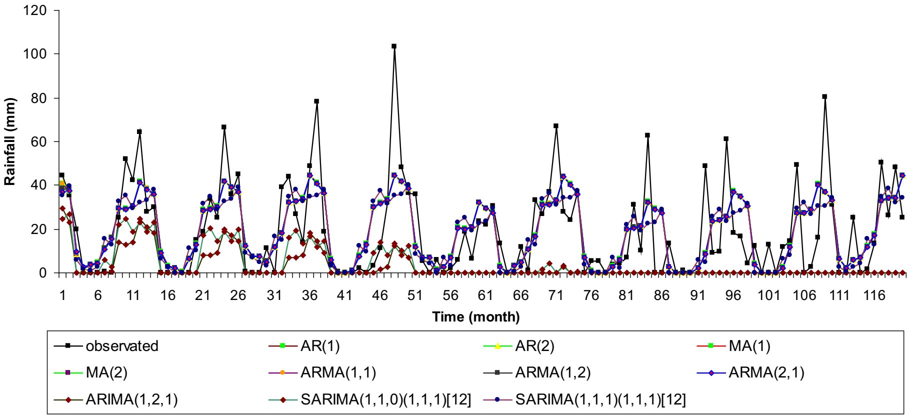

Fig. 9 Models prediction versus observed values in Khoshesfarayen station

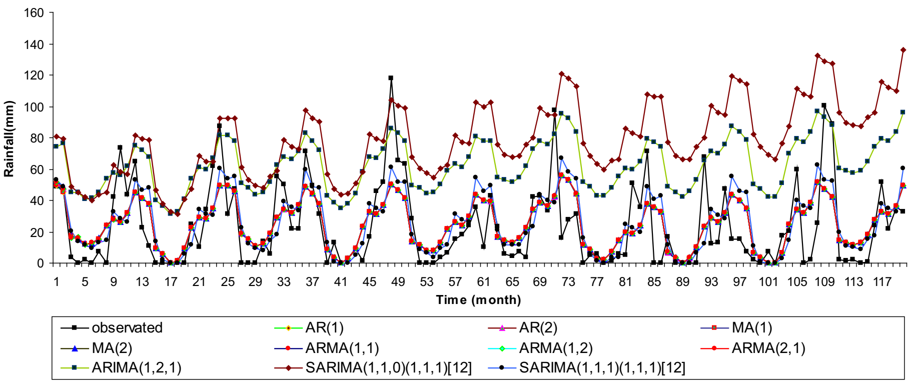

Fig. 10 Models prediction versus observed values in Resalat station

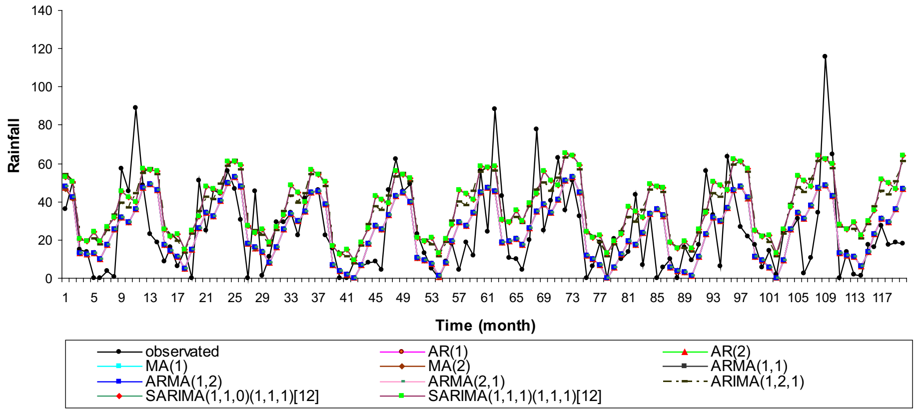

Fig. 11 Models prediction versus observed values in Ruin Araghi station

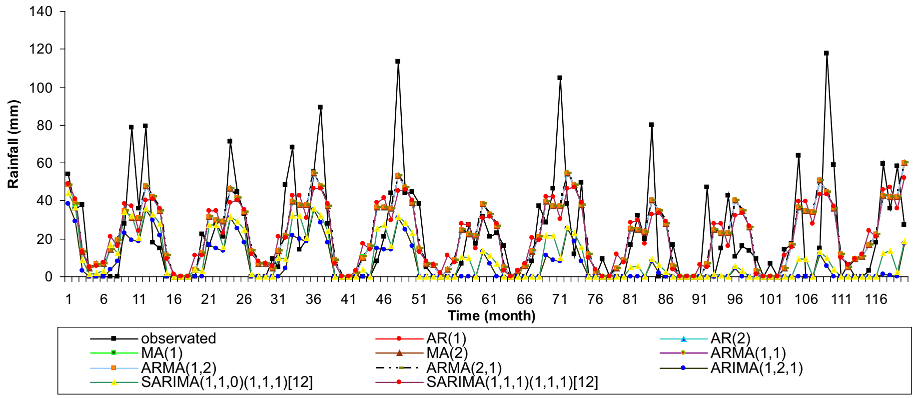

Fig. 12 Models prediction versus observed values in Sankhastdarband station

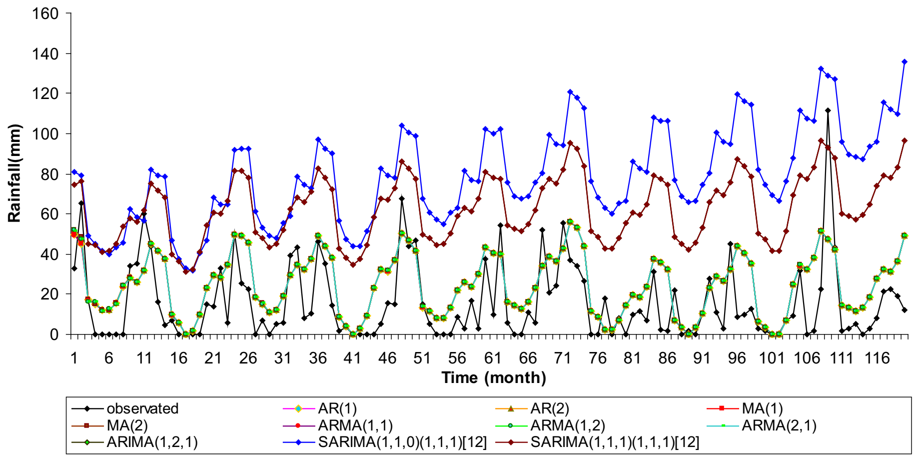

Fig. 13 Models prediction versus observed values in Noshirvan station

models based on Akaike and correlation coefficient, because the Akaike criterion use residual variance which is needed to assess the correlation between the data. Based to the results, stochastic models are one of the most appropriate techniques for prediction of rainfall.

References

Adhikary SK, Mahidur Rahman MD, Das Gupta A (2012) A stochastic modelling technique for predicting groundwater table fluctuations with time series analysis. Int J Appl Sci Eng Res 1(2):238–249

Akrour N, Chazottes A, Mallet C, Barthes L (2014) Simulation of rainfall times series with zero values and realistic statistical distribution in a universal multifractal framework. Geophys Res Abstr 16:2014–6235

Behnia N, Rezaeian F (2015) Coupling wavelet transform with time series models to estimate groundwater level. Arab J Geosci 8(10):8441–8447

Box GEP, Jenkins GM, Reinsel GC (1994) Time series analysis: forecasting and control. Upper Saddle River, NJ

Bras RL, Rodriguez-Iturbe I (1985) Random functions and hydrology. Addison-Wesley, Reading, MA

Brockwell PJ, Davis RA (1996) Introduction to time series and forecasting. Springer, New York

Brockwell PJ, Davis RA (2010) Introduction to time series and forecasting. Springer, New York

Chatfield C (2001) Time-series forecasting. Chapman & Hall/CRC, New York

Delleur JW, Tao PC, Kavass ML (1976) An evaluation of practicality and complexity of some rainfall and runoff time series models. Water Resour Res 12:953–970

Durdu OF (2010) Application of linear stochastic models for drought forecasting in the Büyük Menderes river basin, western Turkey. Stoch Env Res Risk Assess 24(8):1145–1162

Dutta D, Wendy D, Welsh JV, Shaun SHK, Nicholls D (2012) A comparative evaluation of short-term stream flow forecasting using time series analysis and rainfall-runoff models in water source. Water Resour Manage 26:4397–4415. doi:10.1007/s11269-012-0151-9

Erdem E, Shi J (2011) ARMA based approaches for forecasting the tuple of wind speed and direction. Appl Energy 88(4):1405–1414

Faruk D (2010) A hybrid neural network and ARIMA model for water quality time series prediction. Eng Appl Artif Intell 23(4):586–594. doi:10.1016/j.engappai.2009.09.015

Feng Q, Wen X, Li J (2015) Wavelet analysis-support vector machine coupled models for monthly rainfall forecasting in arid regions. Water Resour Manage 29(4):1049–1065

Hannan EJ (1971) Multiple time series. Wiley, New York, p 536

Hipel KW, McLeod AE (1994) Time series modeling of water resources and environmental systems. Elsevier, Amsterdam

Hu Sh (2007) Akaike information criterion, enter for research in scientific computation. North Carolina State University, Raleigh, NC, p 19

Javidi Sabbaghian R, Sharifi MB (2009) Random modeling application in river flow simulation and estimation of mean annual river discharge by time series analysis. International conference on water resources (ICWR). Shahrood, Iran, August 15–17

Khadar Babu SK, Karthikeyan K, Ramanaiah MV, Ramanah D (2011) Prediction of rain-fall flow time series using auto-regressive models. Adv Appl Sci Res 2(2):128–133

Kim SJ, Hyun Y, Lee KK (2005) Time series modeling for evaluation of groundwater discharge rates into an urban subway system. Geosci J 9(1):15–22. doi:10.1007/BF02910550

Klose Ch, Pircher M, Sharma S (2004) Univariate time-series forecasting. 406347/UK "Ökonometrische Prognose" in SS04

Kumar Nanda S, Prasad Tripathy D, Kumar Nayak S, Mohapatra S (2013) Prediction of rainfall in India using Artificial Neural Network (ANN) models. Int J Intell Syst Appl 5(12):1–22. doi:10.5815/ijisa.2013.12.01

Kwon HH, Lall U, Khalil AF (2007) Stochastic simulation model for nonstationary time series using an autoregressive wavelet decomposition: applications to rainfall and temperature. Water Resour Res 43(5):1–15. doi:10.1029/2006WR005258

Lin GF, Lee FC (1992) An aggregation-disaggregation approach for hydrologic time series modelling. J Hydrol 138(3–4):543–557. doi:10.1016/0022-1694(92)90136-J

Mair A, Fares A (2011) Time series analysis of daily rainfall and streamflow in a volcanic dike-intruded aquifer system, O'ahu, Hawai'i, USA. Hydrogeol J 19:929–944. doi:10.1007/s10040-011-0740-3

Mansour MM, Barkwith A, Hughes AGN (2011) A simple overland flow calculation method for distributed groundwater recharge models. Hydrol Process 25(22):3462–3471. doi:10.1002/hyp.8074

Mirzavand M, Ghazavi R (2015) A stochastic modelling technique for groundwater level forecasting in an arid environment using time series methods. Water Resour Manage. doi:10.1007/s11269-014-0875-9

Mirzavand M, Sadatinejad SJ, Ghasemieh H, Imani R, Soleymani Motlagh M (2014) Prediction of ground water level in arid environment using a non-deterministic model. J Water Resour Prot 6:669–676. doi:10.4236/jwarp.2014.67064

Mondal MS, Wasimi SA (2007) Choice of model type in stochastic river hydrology hydrology. In: Proceedings of the 1st international conference on water and flood management (ICWFM), March 12–14, Dhaka, Bangladesh

Nirmala M, Sundaram SM (2010) Modeling and predicting the monthly rainfall in Tamilnadu as a seasonal multivariate ARIMA process. Int J Comput Eng Technol 1(1):103–111

Pebesma EJ, Switzer P, Loague K (2005) Error analysis for the evaluation of model performance: rainfall–runoff event time series data. Hydrol Process 19:1529–1548. doi:10.1002/hyp.5587

Poormohammadi S, Malekinezhad H, Poorshareyati R (2013) Comparison of ANN and time series appropriately in prediction of ground water table (case study: Bakhtegan basin). Water Soil Conserv 20(4):251–262

Radhakrishnan P, Dinesh S (2006) An alternative approach to characterize time series data: case study on Malaysian rainfall data. Chaos Solitons Fractals 27:511–518. doi:10.1016/j.chaos.2005.04.030

Saeidian Y, Ebadi H (2004) Determine the time series of data flow (case study: Vanyar station in the river basin Ajichai). 2nd Students conference on soil and water resources, Shiraz, Iran, May 12–13

Said SM, Manjang S, Wihardi Tjaronge M, Arsyad TM (2013) Arima application as an alternative method of rainfall forecasts in watershed of hydro power plant. Int J Comput Eng Res 3(9):68–73

Salas JD, Fernandez B (1993) Models for data generation in hydrology: univariates techniques. In: Macro JB, Harboe R, Salas JD (eds) Stochastic hydrology and its use in water resources systems simulation and optimization. NATO Advanced Study Institute, Kluwer Academic Publishers, Boston, pp 47–73

Schaars F, Von Asmuth DC (2012) Software for hydrogeologic time series analysis, interfacing data with physical insight. Environ Model Softw 38:178–190. doi:10.1016/j.envsoft.2012.06.003

Seed AW, Draper C, Srikanthan R, Menabde M (2000) A multiplicative broken-line model for time series of mean areal rainfall. Water Resour Res 36(8):2395–2399

Shamshirband Sh, Gocic M, Petkovi D, Saboohi H, Herawan T, Mat Kiah L, Akib Sh (2015) Soft-computing methodologies for precipitation estimation: a case study. IEEE J Select Top Appl Earth Obs Remote Sens 8(3):1353–1358. doi:10.1109/JSTARS.2014.2364075

Shirmohammadi B, Vafakhah M, Moosavi V, Moghaddamnia A (2013) Application of several data-driven techniques for predicting groundwater level. Water Resour Manag 27:419–432. doi:10.1007/s11269-012-0194-y

Silva MAP (2006) A time series model to predict the runoff ratio of catchments of the Kaluganga basin. J Natl Sci Found Sri Lanka 34(2):103–105. doi:10.4038/jnsfsr.v34i2.2089

Sokolnikov AN (2013) THZ identification for defense and security purposes identifying materials, substances and items. World Scientific Publishing CO.Pte. Ltd, Singapore

Soltani S, Modarres R, Eslamian SS (2007) The use of time series modeling for the determination of rainfall climates of Iran. Int J Climatol 27:819–829. doi:10.1002/joc.1427

Venkata Ramana R, Krishna B, Kumar SR, Pandey NG (2013) Monthly rainfall prediction using wavelet neural network analysis. Water Resour Manage 27(10):3697–3711. doi:10.1007/s11269-013-0374-4

Willems P (2009) A time series tool to support the multi-criteria performance evaluation of rainfall-runoff models. Environ Model Softw 24:311–321. doi:10.1016/j.envsoft.2008.09.005

Wu TN, Lee JY, Huang ChH (2010) Application of time series analysis on temporal variation of fluoride in groundwater around southern Taiwan science park. In: 7th international conference on Fuzzy Systems and Knowledge Discovery (FSKD), Yantai, China, August 10–12, 2010