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Modeling streamflow time series using nonlinear SETAR-GARCH models

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ABSTRACT

Although hydrological processes are generally nonlinear, linear time series models are commonly adopted in the field of water sciences. Nonlinear approaches such as threshold time series and conditional heteroscedasticity models are still seldom used. In this study, first, two- and three-regime Self-Exciting Threshold Autoregressive (SETAR) models are used to model the mean behavior of daily streamflows. The residual time series computed from the difference between observations and lag-one time-ahead best-estimates of the fitted models are also obtained. Second, the conditional variance behavior of the residual series obtained from the two- and three-regime SETAR models is modeled using the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model. The GARCH model is hence used to capture the time-varying variance behavior of residuals as a nonlinear phenomenon and thus it removes the existence of autoregressive conditional heteroscedasticity so-called ARCH effect. Finally, the performance of SETAR models and their combination with the GARCH model are evaluated. Six deseasonalized daily streamflow series from upstream watershed rivers of Zarrineh Rood dam, in the southern part of Lake Urmia in Iran, are used to illustrate and test the procedure. The McLeod-Li test, a formal test for demonstrating the ARCH effect, indicates that the ARCH effect exists in all residual series, which means that the residuals of streamflow time series are nonstationary in terms of the variance. Results indicate that the hybrid SETAR-GARCH models performed better than the models without GARCH component. Results demonstrate also that the use of nonlinear SETAR and GARCH improves streamflow modeling efficiency by capturing the heteroscedasticity in the residuals of nonlinear threshold time series.

1. Introduction

In general, two different groups of hydrologic models can be defined: physically-based and mathematically-based models. The physically-based models are sophisticated models that consider a number of parameters and hydro-meteorological variables that affect hydrologic phenomena. On the other hand, mathematical methods represent data-driven models that simulate hydrologic variations based on previously recorded observations. The second group models are simpler to apply in practice due to the easiness of their implementation (Modarres and Ouarda, 2013b). A large number of data-driven techniques can be identified, such as artificial neural networks (ANN), adaptive neuro-fuzzy inference systems (ANFIS), genetic programming (GP), wavelet transforms (WT), machine learning (ML), M5 model tree (M5T), and time series analysis (TSA) models, which have been receiving increasing attention in the field of water resources engineering (Wang et al., 2006; Ouachani et al., 2011; Wang et al., 2017a,b).

Among the above-mentioned data-driven models, TSA models along with the development of their new approaches have always been a major topic in hydrology and water resources engineering for modeling hydrological data (Mohammadi et al., 2006; Fathian et al., 2018). Time series modeling is considered as a useful tool to generate, simulate, forecast and complete hydrological data. Such data enables managers and policy makers in the water sector to make appropriate decisions (Salas et al., 1980). One of the most important hydrological variables that is considered as an important source of hydrological information and is used in a number of water resources engineering applications is streamflow. This variable represents a nonlinear process (Xie et al., 2016) and has a dynamic and complex spatial and temporal structure, which requires more sophisticated tools to model the complexity

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involved (Modarres and Ouarda, 2013b). In this regard, one of the main issues in modeling streamflow process is whether to use a linear or nonlinear approach.

The present work aims to demonstrate the ability of nonlinear time series approaches to provide adequate modeling of streamflows. The complete review and application of other techniques are beyond the scope of this paper. Linear time series models are widely applied for modeling hydroclimatic variables such as rainfall and temperature (Kaushik and Singh, 2008; Helman, 2011; Farajzadeh et al., 2014; Curceac et al., 2018), streamflow (Kisi, 2005; Mohammadi et al., 2006; Can et al., 2012), floods (Shiiba et al., 2000; Zhang and Govindaraju, 2000), droughts (Yurekli and Kurunc, 2004; Modarres, 2007), and water temperature (Ahmadi-Nedushan et al., 2007; Benyahya et al., 2008). Traditional linear models such as the autoregressive integrated moving average (ARIMA) model mainly focus on modeling the mean behavior (first order moment) of the hydrological time series. These linear models are often inadequate because of the variation in residuals, which is not constant in practice. It is commonly assumed that the residual series is an independent identically distributed (i.i.d) normal error (Modarres and Ouarda, 2014a). Linear time series methods are hence usually not able to capture the nonlinear properties of processes governing the temporal variation of streamflow processes. Other more complicated models that are able to capture the dynamics of time series more accurately have therefore been considered (Modarres and Ouarda, 2013c, 2014b).

Recently, there has been a growing interest in the application of nonlinear time series models in hydrology. Threshold autoregressive (TAR) and generalized autoregressive conditional heteroscedasticity (GARCH) methods are commonly used in modeling the mean (first order moment) and the variance (second order moment) of financial and economic time series, respectively (Mohammadi and Su, 2010). The nonlinear TAR approach, which is commonly referred to as piecewise linear or regime-switching model, can model the mean behavior of hydrologic time series (Tong, 1983). However, the GARCH approach can model the time-varying variance behavior in the residual series from TAR approach fitted to hydrologic time series. There is usually an ARCH or GARCH effect in a time series when the time series exhibits autoregressive conditional heteroscedasticity. The conditional heteroscedasticity means the time-varying variance (i.e. volatility), or the second order moment, of the residual time series. In the volatility behavior of the residuals, large changes tend to follow large changes and small changes tend to follow small changes (Wang et al., 2005). For this reason, this behavior is called conditional heteroscedasticity that can be captured using ARCH-type models because the conditional heteroscedasticity of the residual time series exhibits autoregressive structure (Wang et al., 2005). These models include the ARCH and GARCH methods, which were respectively proposed by Engle (1982) and Bollerslev (1986), and allow to eliminate the ARCH effect. These types of models have not yet received considerable attention from the hydrological community. The TAR and GARCH approaches have been slowly gaining popularity to model hydro-meteorological variables nowadays.

Amendola and Storti (1999) used the TAR approach to model the switching between different regimes using the antecedent precipitation index. Amendola (2003) compared the performance of a number of TAR models for river flow forecasting. Komorník et al., (2006) evaluated the performance of nonlinear two-regime TAR models for mean monthly streamflow data in a mountain region in Slovakia. A new type of TAR model was proposed by them and tested and the results showed its superior predictive performance. Romilly (2005) applied a seasonal ARIMA approach to model the mean behavior of global mean monthly temperature and a GARCH approach to capture the temporal variability of the variance of residual series. The results of this study indicated that the hybrid seasonal ARIMA-GARCH model leads to improved performances in comparison to the seasonal ARIMA model. Wang et al., (2005) used an ARMA-GARCH model to capture the ARCH effects in the daily streamflow time series of the upper Yellow River in China. Modarres and Ouarda (2013a) used hybrid seasonal ARIMA-GARCH to model the heteroscedasticity in the residuals of the seasonal ARIMA model for two monthly rainfall time series from humid and arid regions. Their results showed that the GARCH approach gives a better performance, and that the modelling procedure can stabilize the heteroscedasticity of rainfall time series. Modarres and Ouarda (2013c) introduced three types of GARCH models in streamflow time series modeling, and their results suggested that using GARCH-type models allows capturing the heteroscedasticity in the residuals of ARIMA models and improving the modeling efficiency.

Previous studies have mainly focused on linear time series models for modeling the mean behavior of streamflow time series whereas this process does not exhibit a linear behavior. In this regard, streamflow processes cannot be well fitted by the popular linear models such as ARIMA compared to nonlinear models such as TAR (Komorník et al., 2006; Järas and Gishani, 2010; Amiri, 2015). Therefore, potential improvement may result from modeling the mean and the variance behavior of streamflow time series using nonlinear TAR and GARCH models. As far as the authors are aware, the use and performance evaluation of nonlinear two-regime and three-regime (multiple-regime) TAR models and their combination with the GARCH approach (TAR-GARCH error model) have not yet been explored for modeling streamflow time series. The present study aims to test and evaluate the performance of Self-Exciting Threshold Autoregressive (SETAR) models and their combination with the GARCH approach in modeling daily streamflow time series. SETAR models represent a special case and the main type of TAR models and were first introduced by Tong (1983). The data used is the daily streamflow time series from six upstream watershed rivers of Zarrineh Rood dam, in the southern part of Lake Urmia in Iran. The paper also examines the performance of SETAR models with/without GARCH approach using various criteria developed to handle nonlinearity and heteroscedasticity. The paper is organized as follows: The case study is described in Section 2 of the document. The methodology of the study and the theoretical presentation of the approaches considered in this research are illustrated in Section 3. A description and discussion of the results are illustrated in Section 5. Finally, the conclusions are presented in Section 6.

2. Study area and data

The case study deals with the headwaters of the Zarrineh Rood River located upstream of the Zarrineh Rood dam. The study basin represents one the biggest sub-basins of Lake Urmia. This basin is located in the southern part of Lake Urmia, in northwestern Iran with an area of 7081 km^2 (Fig. 1). The length of the Zarrineh Rood River is approximately 230 km. the river discharges into Lake Urmia and represents the source of the majority of the Lake's water budget (UNEP, 2012; Ahmadzadeh et al., 2016). The elevation of the study area varies between 1746 and 2121 m a.s.l. The headwaters of this river along with all its main tributaries arise from the mountains of the Kurdistan and West Azarbaijan provinces. The region receives substantial amounts of snow during the winter season (Ahmadzadeh et al., 2016). The study area is constituted of four sub-basins namely, Saghez Chai, Jighato Chai, Khorkhoreh Chai and Sarogh Chai from west to east, respectively, which discharge water into the Zarrineh Rood dam reservoir (Fig. 1).

In the present study, the available daily average streamflow records of six streamflow gauging stations were used. Continuous 15 years of daily observations from the 1st of January 1997 to the 31st of December 2011 were used to compare the modeling capabilities of different SETAR-GARCH models in terms of the mean and conditional heteroscedasticity of streamflow time series. The geographical distributions of the hydrometric stations and their important characteristics are shown in Fig. 1 and in Table 1, respectively. The abbreviations of the hydrometric stations presented in Table 1 were used instead of their names in the rest of the paper.

Fig. 1. Geographic location of the rivers and streamflow gauging stations in the study area.

Before building the SETAR model, the original streamflow time series are transformed to a deseasonalized time series. This transformation is performed in order to (1) avoid the effect of seasonality on the conditional heteroscedasticity because, according to Wang et al., (2005), the ARCH effect can be partly caused by seasonal variations (seasonality) of daily streamflows, (2) develop a better fit of the applied models, (3) normalize the time series in respect to the variance (make it more homoscedastic), and to (4) reduce the scale effect, i.e. increase the importance of smaller values and reduce the impact of larger values (Salas et al., 1980; Järas and Gishani, 2010).

The deseasonalized (standardized) procedure includes two steps. First, a logarithmic transformation is applied to the daily streamflows. Second, the logarithmically transformed series is standardized by subtracting the seasonal daily mean values from the data and dividing the resulting values by their own seasonal standard deviations (Wang et al., 2005). However, before standardization, streamflow time series are

Table 1
List of streamflow gauging stations used in the study.

Stations name	Location	Stations name in text	Latitude (degree)	Longitude (degree)	Elevation (m)	Drainage area (km^2)	Mean discharge (m^3/s)
Ghabghablou	Saghez Chai River	"GH"	36.18N	46.17 E	1500	661	7.58
Darepanbedan	Saghez Chai River	"D"	36.28N	46.37 E	1470	1041	7.77
Pol Gheshlagh	Jighato Chai River	"PG"	36.10N	46.35 E	1436	1091	10.10
Pol Anian	Jighato Chai River	"PA"	36.20N	46.43 E	1460	1328	11.47
Sonnateh	Khorkhoreh Chai River	"S"	36.17N	46.55 E	1434	1233	7.76
Safakhaneh	Sarogh Chai River	"SK"	36.40N	46.70 E	1475	2209	6.23

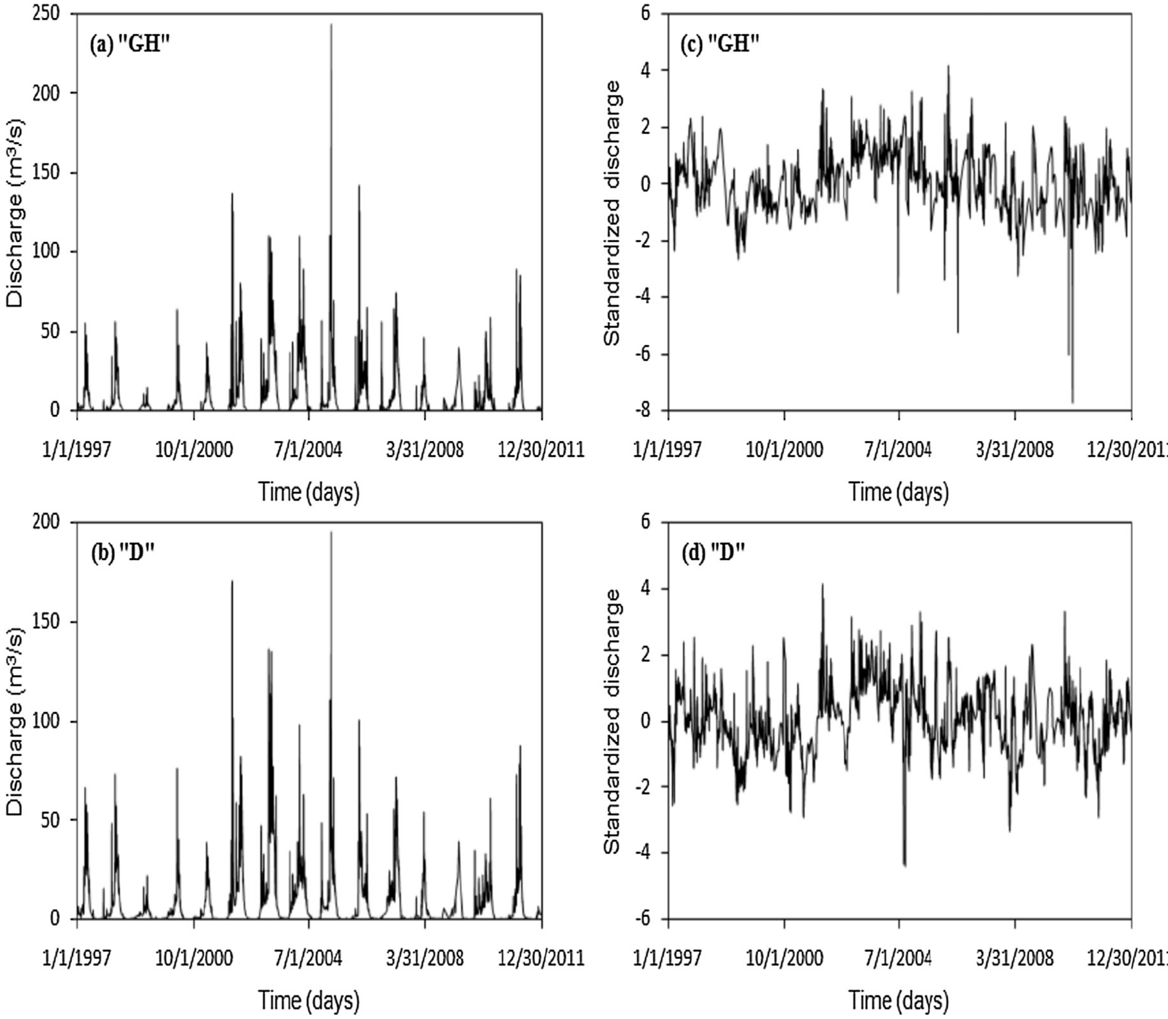

Fig. 2. Examples of daily streamflow (m^3/s) at the "GH" and "D" stations (a, b), and the corresponding deseasonalized series (c, d).

smoothed using Fourier harmonics to alleviate the stochastic fluctuations of the daily means and standard deviations according to the procedure proposed by Salas et al. (1980) and applied by Fathian et al. (2018) for the streamflow data used in this study.

The procedure is illustrated by two time series plots (Fig. 2a and b) corresponding to the discharge series at the upstream site ("GH" station) and the downstream site ("D" station) as well as their corresponding deseasonalized series (Fig. 2c and d). No trends are detected in Fig. 2a and b. However, the annual seasonality is obvious within these data series. A strong correlation can also be observed between the series corresponding to the two sites.

3. Methods

In this section, the methodology for building the nonlinear SETAR-GARCH models for streamflow time series is explained. The flow chart (Fig. 3) provides more details concerning the different stages of the streamflow modeling process.

3.1. Testing procedures for stationarity and threshold nonlinearity

Before building the nonlinear SETAR model, the stationarity and nonlinearity of the deseasonalized streamflow series were tested using the Augmented Dickey Fuller (ADF) test and the likelihood ratio test (TLRT), respectively (Dickey and Fuller, 1979; Chan, 1991). The ADF test allows testing the presence of a unit root in intended time series based on considering an autoregressive AR(1) model. If the autoregressive parameter (i.e., unit root) of the AR(1) model is equal to one, the intended time series is considered a non-stationary process (null hypothesis), otherwise, it is considered stationary. The TLRT test is useful to detect threshold nonlinearity based on considering an AR(p) and a multiple-regime TAR model of order p. The null hypothesis of the TLRT approach for threshold nonlinearity is that the fitted model to the time series is an AR(p) model. The alternative hypothesis is that the fitted model to the time series is a TAR model with an order p autoregressive process for each regime (Cryer and Chan, 2008). For more details about the formulations of these tests, the reader is referred to Modarres and Ouarda (2013b) and Cryer and Chan (2008).

3.2. Nonlinear TAR model

The TAR model belongs to a group of nonlinear regime-switching models. The basic idea of these nonlinear time series models is that certain properties of the time series (such as its mean, variance and autocorrelation) are different in various regimes of the modeled process (Cryer and Chan, 2008; Tsay, 2010). The Self-Exciting Threshold Autoregressive (SETAR) model is a special case of the TAR model (Tong, 1983).

According to the assumptions of TAR-type models, the movements between regimes are controlled by a parameter called "threshold". In the case of the SETAR model, the threshold parameter is a certain lagged value of the intended time series itself, or an endogenous

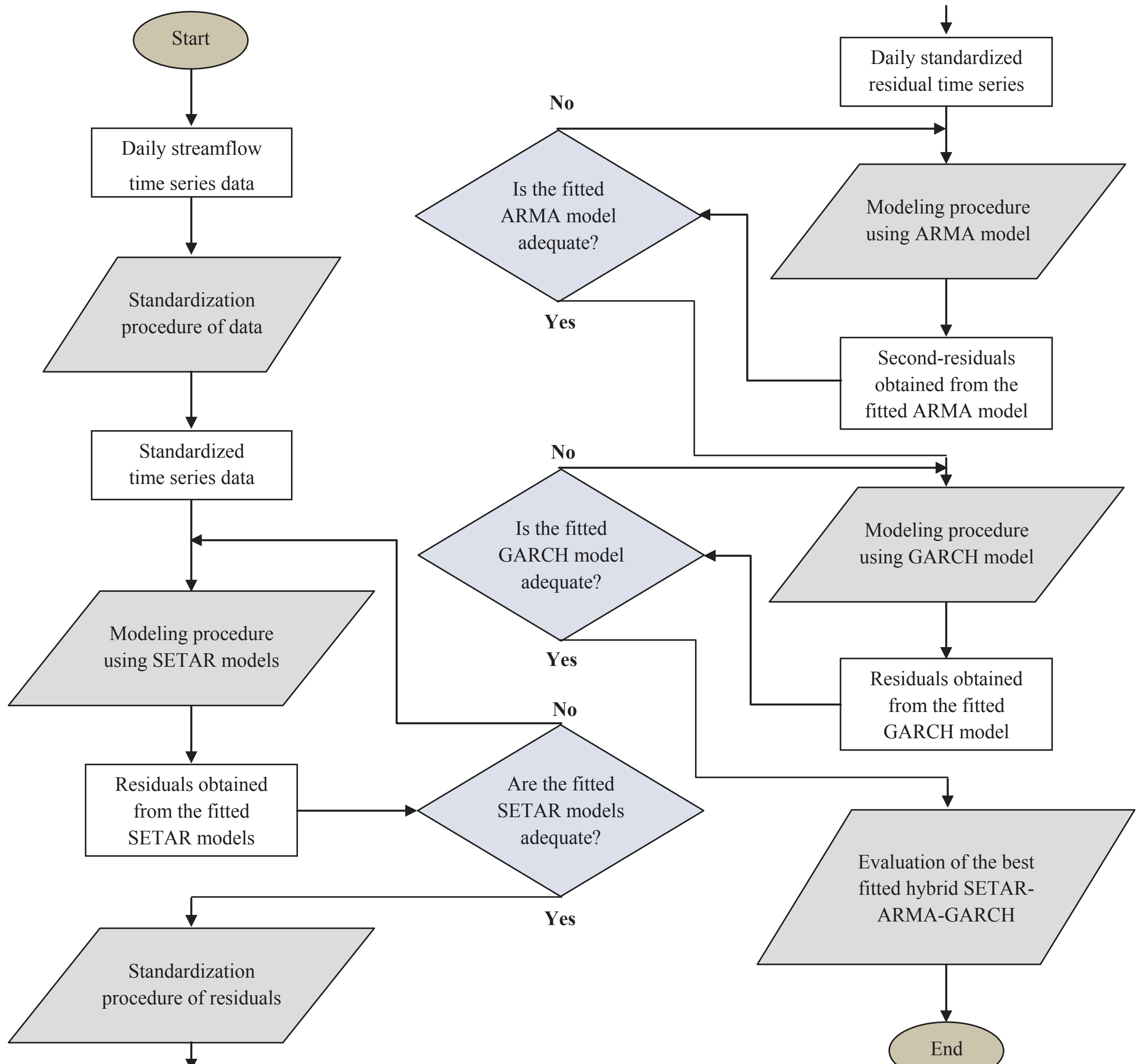

Fig. 3. Flow chart of the streamflow modeling process.

parameter (Komorník et al., 2006). Suppose that the intended time series data set is $(Y_1,\ldots,Y_n)$, where n is the length of the time series, then, a two-regime SETAR model, denoted as SETAR(2; p, r), can be written as follows:

$$Y_t = \begin{cases} \varphi_0^{(1)} + \sum_{i=1}^{p} \varphi_i^{(1)} Y_{t-i} + \varepsilon_t^{(1)} & \text{if } Y_{t-d} \leqslant \tau \\ \varphi_0^{(2)} + \sum_{i=1}^{r} \varphi_i^{(2)} Y_{t-i} + \varepsilon_t^{(2)} & \text{if } Y_{t-d} > \tau \end{cases} \quad (1)$$

where $\varphi_i^j\,(i \in \{1, 2, \ldots, p\},\ i \in \{1, 2, \ldots, r\},\ j \in \{1, 2\})$ are the coefficients of the AR models, p and r are the orders of the AR models for lower and upper regimes in a two-regime SETAR model, ε_t is the residual value at time t, i.e. the difference between observation (Y_t) and lag-one time-ahead best-estimate of the fitted model ($\hat{Y}_t$) at time t, that $\varepsilon_t \tilde{N}(0, \sigma^2)$, d is a lag time, and τ is the threshold value (transition parameter). Using Eq. (1), a three-regime SETAR model, denoted as SETAR(3; p, r, q), can be developed and represented as follows:

$$Y_t = \begin{cases} \varphi_0^{(1)} + \sum_{i=1}^{p} \varphi_i^{(1)} Y_{t-i} + \varepsilon_t^{(1)} & \text{if } Y_{t-d} \leqslant \tau_1 \\ \varphi_0^{(2)} + \sum_{i=1}^{r} \varphi_i^{(2)} Y_{t-i} + \varepsilon_t^{(2)} & \text{if } \tau_1 < Y_{t-d} \leqslant \tau_2 \\ \varphi_0^{(3)} + \sum_{i=1}^{q} \varphi_i^{(3)} Y_{t-i} + \varepsilon_t^{(3)} & \text{if } Y_{t-d} > \tau_2 \end{cases} \quad (2)$$

where $\varphi_i^j\,(i \in \{1, 2, \ldots, p\},\ i \in \{1, 2, \ldots, r\},\ i \in \{1, 2, \ldots, p\},\ j \in \{1, 2, 3\})$ are the coefficients of the AR models, p, r and q are the orders of the AR models for lower, middle and upper regimes in a three-regime SETAR model, and τ_1 and τ_2 are the threshold values (Cryer and Chan 2008; Tsay 2010).

In order to estimate a time series with a fitted two-regime SETAR model, for example, it is essential to know the threshold parameter τ and the delay parameter d. Then, the data sets can be split into two parts; according to whether or not $Y_{t-d} \leqslant \tau$. In this regard, the data larger and smaller than the threshold values are identified and each regime can be estimated as a common AR model. The appropriate orders of the AR model can then be estimated by minimizing the Akaike information criterion (AIC) for a fixed τ and d as (Cryer and Chan, 2008):

Table 2
Stationarity and threshold nonlinearity tests of the deseasonalized streamflow series.

Stations names	Statistics of ADF test	*P*-value of ADF test	Statistics of TLRT test	*P*-value of TLRT test
"GH"	−7.11	< 0.01	16.62	< 0.05
"D"	−7.21	< 0.01	10.87	< 0.05
"PG"	−7.11	< 0.01	8.40	< 0.15
"PA"	−7.15	< 0.01	17.97	< 0.05
"S"	−6.99	< 0.01	31.34	< 0.05
"SK"	−6.77	< 0.01	19.98	< 0.05

$$AIC(p, r, \tau, d) = -2L(\tau, d) + 2(p + r + 2)$$
$$L(\tau, d) = -\frac{n-p}{2}\{1 + \log(2\pi)\} - \frac{n_1(\tau,d)}{2}\log((\hat{\sigma}_1(\tau, d))^2) - \frac{n_2(\tau,d)}{2}\log((\hat{\sigma}_2(\tau, d))^2) \quad (3)$$

where $L(\tau, d)$ is the log-likelihood function to maximize in order to estimate τ and d, n_1 and n_2 are the numbers of data observations in each regime, and $\hat{\sigma}_1$ and $\hat{\sigma}_2$ are the noise or error variances in the lower and upper regimes, respectively. It should be noted that the AR orders in SETAR models do not need to be identical in two-and three-regime models (Cryer and Chan, 2008).

To test the sufficiency of the fitted SETAR model, two formal statistical methods based on the analysis of residuals are discussed in this study. In the first method, the autocorrelation function (ACF) of the obtained residual series from the fitted SETAR model is investigated. The sufficiency of the fitted SETAR model is accepted if all ACF coefficients are located within the confidence intervals. In the second method, the Ljung-Box test is used to check the sufficiency of the SETAR model (Modarres and Ouarda, 2013a; Cryer and Chan, 2008). This test leads to a value *Q*, which follows a chi-square distribution and is given by:

$$Q = N(N + 2)\sum_{k=1}^{L}\frac{r_k^2(\varepsilon)}{(N - K)} \quad (4)$$

where *N* is the length of the residual series, *L* is the number of autocorrelations of residuals between 15 and 25, and r_k is the ACF of the residuals ε, at the lag *k*. If the *Q*-statistic is less than the tabulated value at the considered significance level, then the residual series are uncorrelated and time independent, and the fitted model is acceptable (Modarres and Ouarda, 2013a).

3.3. The GARCH modeling approach

The GARCH model is a privileged approach for modeling volatility in the literature. This model was developed by Bollerslev (1986) to generalize the ARCH model as proposed by Engle (1982). When a SETAR model is fitted to a deseasonalized time series, the obtained residuals from the fitted model may show sufficient fitting, but the squared residual series may still show significant autocorrelation. In other words, while the residuals seem statistically uncorrelated according to the two methods mentioned in the previous subsection, they are not identically distributed, that is, the residuals are not independent and identically distributed (i.i.d.) through time (Wang et al., 2005). Therefore, the heteroscedasticity behavior (the ARCH effect or conditional time-variant variance) may be observed in the residual series. This behavior can be generalized and modeled by a GARCH approach. The resulting model is then named SETAR-GARCH. The GARCH model for a process (ε_t) is defined as follows if its first two conditional moments exist and satisfy (Francq and Zakoian, 2011):

$$\sigma_t^2 = Var(\varepsilon_t|\varepsilon_u, u < t) = \omega + \sum_{i=1}^{V}\alpha_i\varepsilon_{t-i}^2 + \sum_{j=1}^{M}\beta_j\sigma_{t-j}^2 \quad (5)$$

$$\varepsilon_t = \sigma_t e_t \quad e_t \sim Normal(0, 1)$$
$$\varepsilon_t|\psi_{t-1} \sim Normal(0, \sigma_t^2) \quad (6)$$

where σ_t^2 ($Var(\varepsilon_t|\varepsilon_u, u < t)$) is the conditional time-variant variance of the residual series, ω is a constant, $\alpha_1, ...,\alpha_V$ and $\beta_1, ...,\beta_M$ are the coefficients of the GARCH (*V*,*M*) approach, and *V* and *M* are the orders of the coefficients. Based on the GARCH (*V*,*M*) model, the conditional variance of ε_t, i.e., σ_t^2, depends on the *V* past squared residuals, and the *M* lagged conditional variance. The order of the GARCH model is determined by the AIC technique and the parameters of the model can be estimated using the maximum likelihood estimation (MLE) method (Cryer and Chan, 2008).

In order to identify and check the existence of heteroscedasticity in the residual series, Bollerslev (1986) relied on the ACF of standardized squared residuals (SSRs). This technique is helpful for identifying and checking GARCH behavior in SSRs (Wang et al., 2005). The McLeod-Li test (McLeod and Li, 1983) is used in this study for the ARCH effect. Similar to equation (4) for the Ljung-Box test *Q*-statistic, the McLeod-Li *Q*-statistic is given by:

$$Q = N(N + 2)\sum_{k=1}^{L}\frac{r_k^2(\varepsilon^2)}{(N - K)} \quad (7)$$

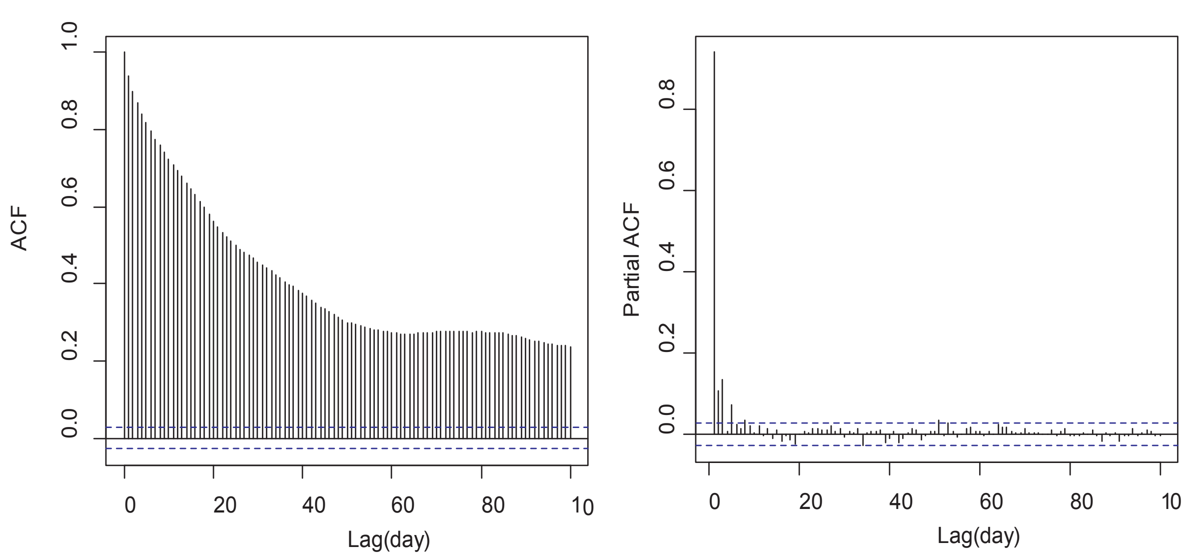

Fig. 4. ACF and PACF of deseasonalized daily streamflow series at "GH" station.

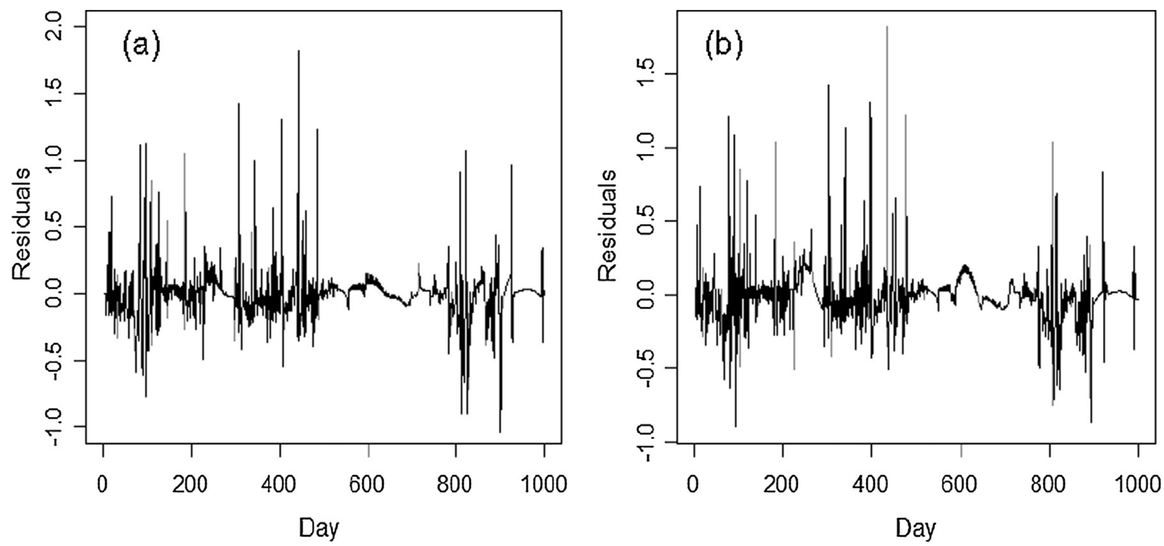

Fig. 5. Segments of the two residual series from (a) SETAR(2;4,5) model and (b) SETAR(3;5,1,3) model for daily streamflows at "GH" station.

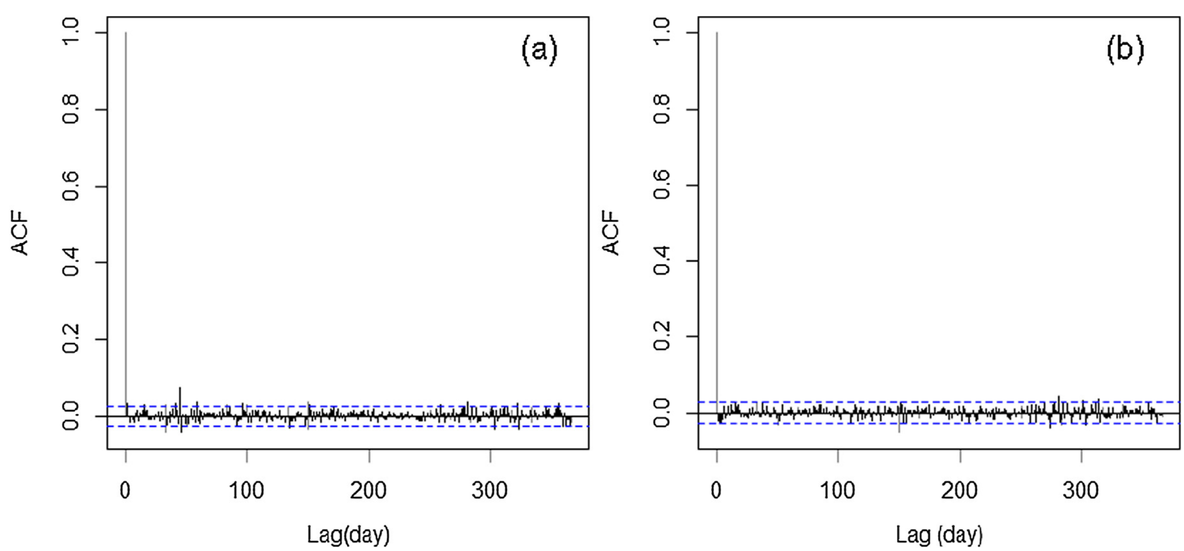

Fig. 6. ACFs of the two residual series from (a) SETAR(2;4,5) model and (b) SETAR(3;5,1,3) model for daily streamflows at "GH" station.

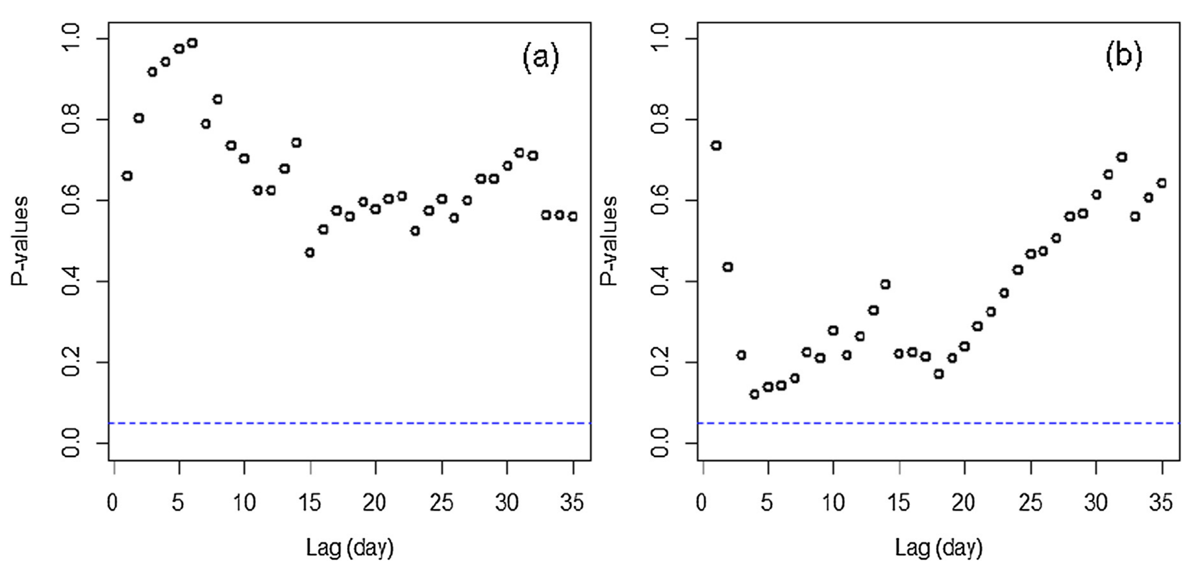

Fig. 7. *P*-values of the Ljung-Box test of the two residual series from (a) SETAR(2;4,5) model and (b) SETAR(3;5,1,3) model for daily streamflows at "GH" station.

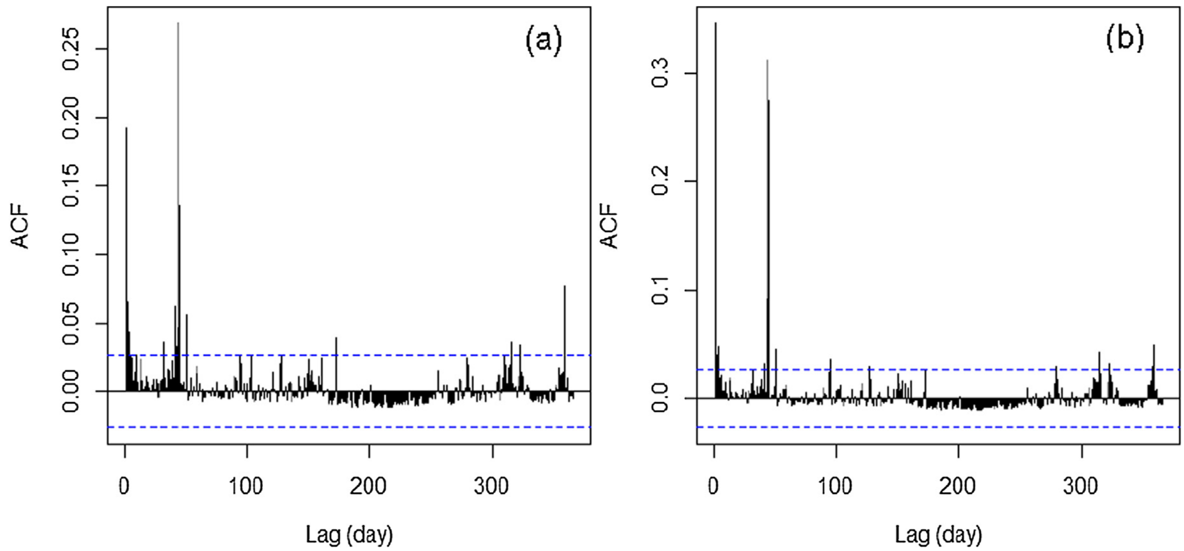

Fig. 8. ACFs of the two squared residual series from (a) SETAR(2;4,5) model and (b) SETAR(3;5,1,3) model for daily streamflows at "GH" station.

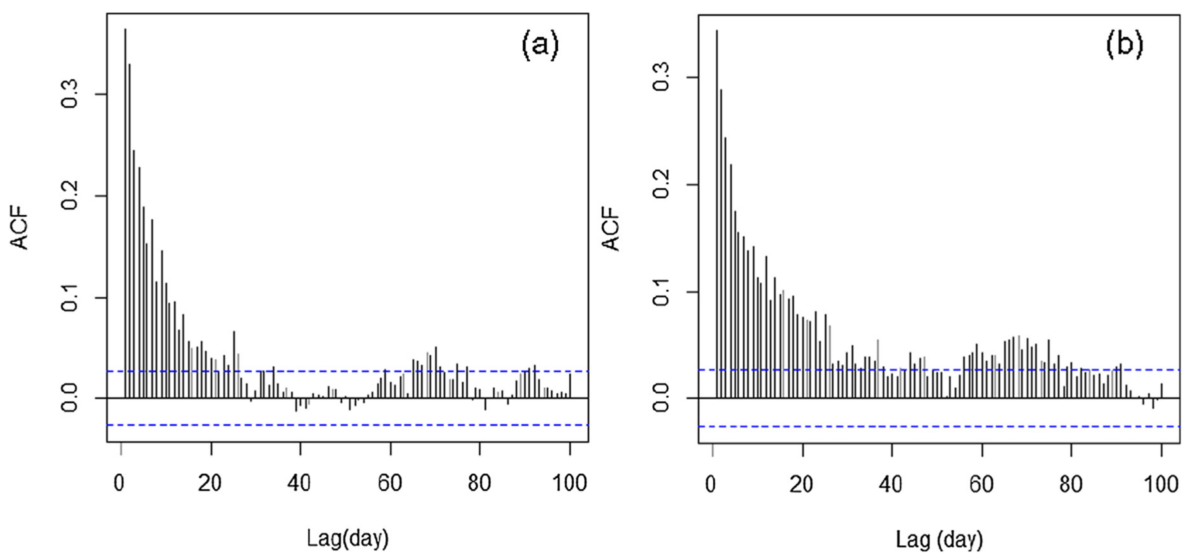

Fig. 9. ACFs of the two squared seasonally standardized residual series from (a) SETAR(2;4,5) model and (b) SETAR(3;5,1,3) model for daily streamflows at "GH" station.

The assumption of no GARCH effect (as null hypothesis) for the residual series is accepted if the calculated *Q*-statistic is lower than the tabulated value at a given significance level (Modarres and Ouarda, 2013a).

3.4. Comparative evaluation methods

Evaluation methods can give important guidance in order to choose the appropriate models. The performance of alternative models can be examined by means of a set of evaluation metrics. The evaluation metrics used in the present study are:

- Absolute Maximum Error:

$$AME = \max(|Q_i - \widehat{Q}_i|) \quad (8)$$

- Peak Difference:

$$PDIFF = \max(Q_i) - \max(\widehat{Q}_i) \quad (9)$$

- Mean Absolute Error:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |\widehat{Q}_i - Q_i| \quad (10)$$

- Root Mean Squared Error:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(Q_i - \widehat{Q}_i)^2}{n}} \quad (11)$$

- Relative Absolute Error:

$$RAE = \frac{\sum_{i=1}^{n}|Q_i - \widehat{Q}_i|}{\sum_{i=1}^{n}|Q_i - \bar{Q}|} \quad (12)$$

- Coefficient of determination (*R*-squared):

$$R^2 = \left[\frac{\sum_{i=1}^{n}(Q_i - \bar{Q})(\widehat{Q}_i - \widetilde{Q})}{\sqrt{\sum_{i=1}^{n}(Q_i - \bar{Q})^2 \sum_{i=1}^{n}(\widehat{Q}_i - \widetilde{Q})^2}}\right] \quad (13)$$

The metrics selected are in three categories, namely, metrics that calculate absolute errors such as AME, PDIFF, MAE and RMSE; metrics

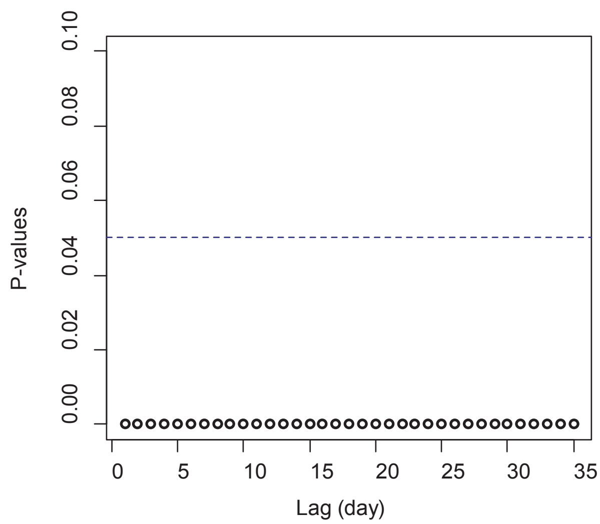

Fig. 10. McLeod-Li test for seasonally standardized residual series from the two- and three-regime SETAR models for daily streamflows at "GH" station.

that calculate relative errors such as RAE; and dimensionless metrics such as R^2. In the above equations, Q_i and $\widehat{Q}_i$ are the observed and estimated time series, and $\bar{Q}$ and $\widetilde{Q}$ are their means, respectively (Modarres and Ouarda 2013a, b). The statistics software R was used in all statistical computations in this study (R Core and Team, 2013).

4. Results and discussion

4.1. Nonlinear SETAR models

Before discussing the results of the SETAR models, it is important to carry out the hypothesis testing. The results of the ADF and TLRT tests (Table 2) showed that all series are stationary, and that threshold nonlinearity exists at a specified significance level. Therefore, the SETAR models can be fitted to the daily streamflow time series.

As indicated, for the two- and three-regime SETAR models, the threshold and delay parameters are first estimated. Then, the orders of the AR model are determined for each regime. Finally, the most appropriate models are selected. As an illustration, for the "GH" station the SETAR(2;4,5) and SETAR(3;5,1,3) models are selected through the examination of the ACF and partial ACF (PACF) of the deseasonalized streamflow series (Fig. 4) and comparison of AIC values. The segments of the two residual series obtained from the two SETAR models are shown in Fig. 5.

The ACFs of two residual series and *P*-value plots of the Ljung-Box test are illustrated in Figs. 6 and 7. They indicate that the fitted two- and three-regime SETAR models are sufficient and valid for daily streamflows at "GH" gauging station. Therefore, the null hypothesis of these two statistical methods, i.e., no autocorrelation structure in the residuals or verification of model sufficiency, is accepted at the 5% significance level, and the residual series are time-independent. This modeling procedure is repeated for each hydrometric station, and the most appropriate multiple-regime SETAR models are determined.

4.2. Tests for nonlinear GARCH model

When the mean behavior of a time series is modeled using a non-linear SETAR model, it is assumed that the residuals follow a time-i.i.d behavior. According to Wang et al. (2005), the residual series may indeed represent statistically uncorrelated behavior (Fig. 6), but they are not identically distributed from a visual point of view (Fig. 5). This means that the residual series do not have an i.i.d behavior through time. This can be observed during several periods of residual behavior (Fig. 5), where large variations of residuals tend to follow large variations, and small variations of residuals tend to follow small variations. Therefore, we can infer the existence of a common behavior of GARCH processes, the so-called conditional heteroscedasticity or volatility, in daily streamflow series (Wang et al., 2005).

The GARCH behavior was identified by examining the ACF of squared residual series. As an example, Fig. 8 illustrates the ACFs structure of squared residual series from the SETAR(2;4,5) and SETAR (3;5,1,3) models for daily streamflows at "GH" station. It can be observed that the two squared residual series are autocorrelated, and this indicates that the variances of residual series are time-dependent. Therefore, the existence of an ARCH effect can be confirmed in the residual series.

Furthermore, according to Wang et al. (2005), there may be seasonal variations in the variance structure of residual series and this can be removed by standardization of the residual series obtained from SETAR models. Seasonally standardized residual series are calculated by dividing the residual series from the SETAR models for daily streamflows by the daily standard deviations. Then, the existence of the ARCH effect can be checked in the squared seasonally standardized residual series of daily streamflows. As an example, Fig. 9 illustrates the

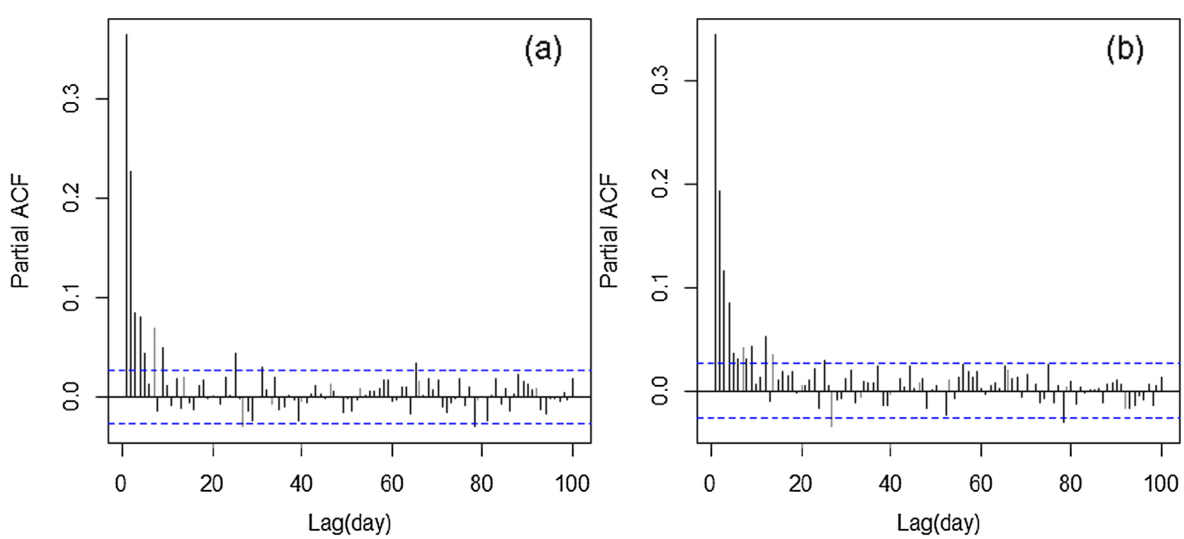

Fig. 11. PACFs of the two squared seasonally standardized residual series from (a) SETAR(2;4,5) model and (b) SETAR(3;5,1,3) model for daily streamflows at "GH" station.

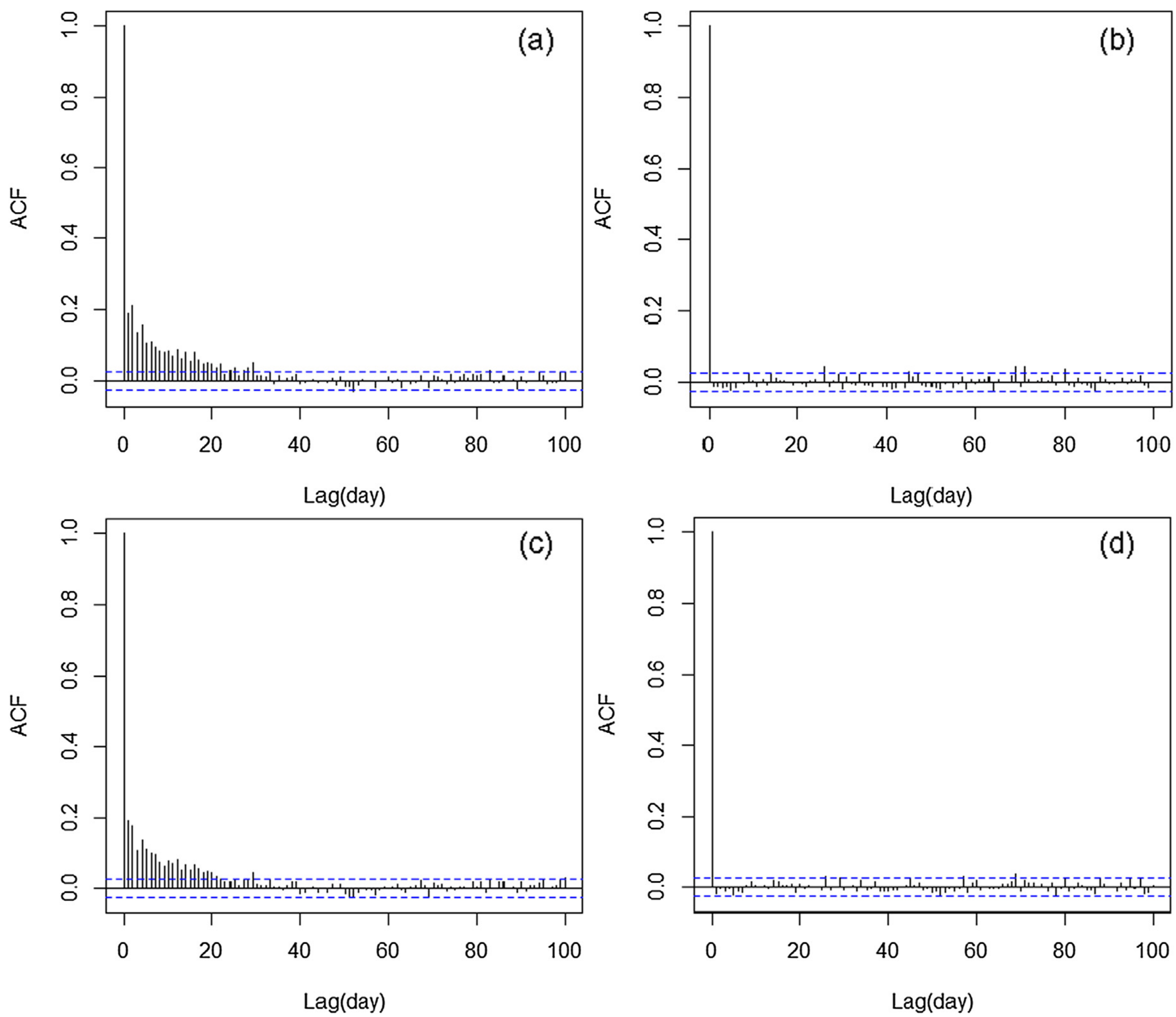

Fig. 12. ACF structure of (a) and (c) the standardized residuals, (b) and (d) the squared standardized residuals from the SETAR(2;4,5)-ARCH(5) and the SETAR(3;5,1,3)-ARCH(7) models, respectively, for daily streamflows at "GH" station.

ACFs structure of squared seasonally standardized residual series from the SETAR(2;4,5) and SETAR(3;5,1,3) models at "GH" station. As observed, after seasonal standardization of the residual series, the ACF's structure of squared seasonally standardized residual series is still significant at 5% level. The standardization in residuals series could partly affect the seasonal variance variations in the squared residual series, but the ARCH effect still exists.

In addition, the McLeod-Li test confirms the existence of the ARCH effect in the squared seasonally standardized residual series from the two- and three-regime models for daily streamflows at "GH" station (Fig. 10). As it can be observed, all *p*-values of the McLeod-Li test are < 5% (significance level), therefore, the null hypothesis of this test is rejected. There are other reasons to show the ARCH effect in daily streamflows, such as including temperature fluctuations as an effective factor for snowmelt and evapotranspiration, and precipitation variations as an important factor for streamflow behavior (Wang et al., 2005).

4.3. Nonlinear hybrid SETAR-GARCH model

The most appropriate two- and three-SETAR models are fitted to the daily deseasonalized streamflow series at "GH" station as an example. The ACFs and PACFs structure in the two squared seasonally standardized residual series from the fitted SETAR models are depicted in Figs. 9 and 11, respectively. Based on choosing the smallest AIC values and ACF and PACF structure, the GARCH(5,0) and GARCH(7,0) models (or in other words, ARCH(5) and ARCH(7) models), respectively, are fitted to the two seasonally standardized residual series from the SETAR(2;4,5) and SETAR(3;5,1,3) models at "GH" station. Therefore, the hybrid two- and three-regime SETAR-GARCH models are detected as sufficient models for modeling conditional mean and conditional variance behaviors of streamflow series.

Fig. 12 presents the ACFs of standardized residuals e_t (Fig. 12a and c), and their squared series (Fig. 12b and d) for the hybrid SETAR(2;4,5)-ARCH(5) and SETAR(3;5,1,3)-ARCH(7) models at "GH" station. Fig. 12b, d indicate that there is no autocorrelation structure in the squared standardized residuals from the hybrid SETAR-ARCH models; thus the ARCH effect was removed. However, there is a significant autocorrelation structure in the non-squared standardized residuals from these hybrid daily streamflow models (Fig. 12a and c). The significant autocorrelation structure in Fig. 12a and c originates from the seasonally standardized residuals established from the building procedure of hybrid SETAR-GARCH models. Fig. 13 presents that the ACF and PACF analyses from the SETAR(2;4,5) and SETAR(3;5,1,3) models for "GH" station – these are significant. Wang et al., (2005) indicated that the distinct mechanism of such significant autocorrelation was not clear. Similar analyses to the one shown in Figs. 12 and 13 are also carried out for all other stations located in this study area.

To address the significant correlation (Fig. 13), the mean behavior in the non-squared seasonally standardized residuals is modelled using an ARMA model. The analysis of the ACFs and PACFs in Fig. 13 lead to an ARMA model, therefore, it is considered as an additional model for

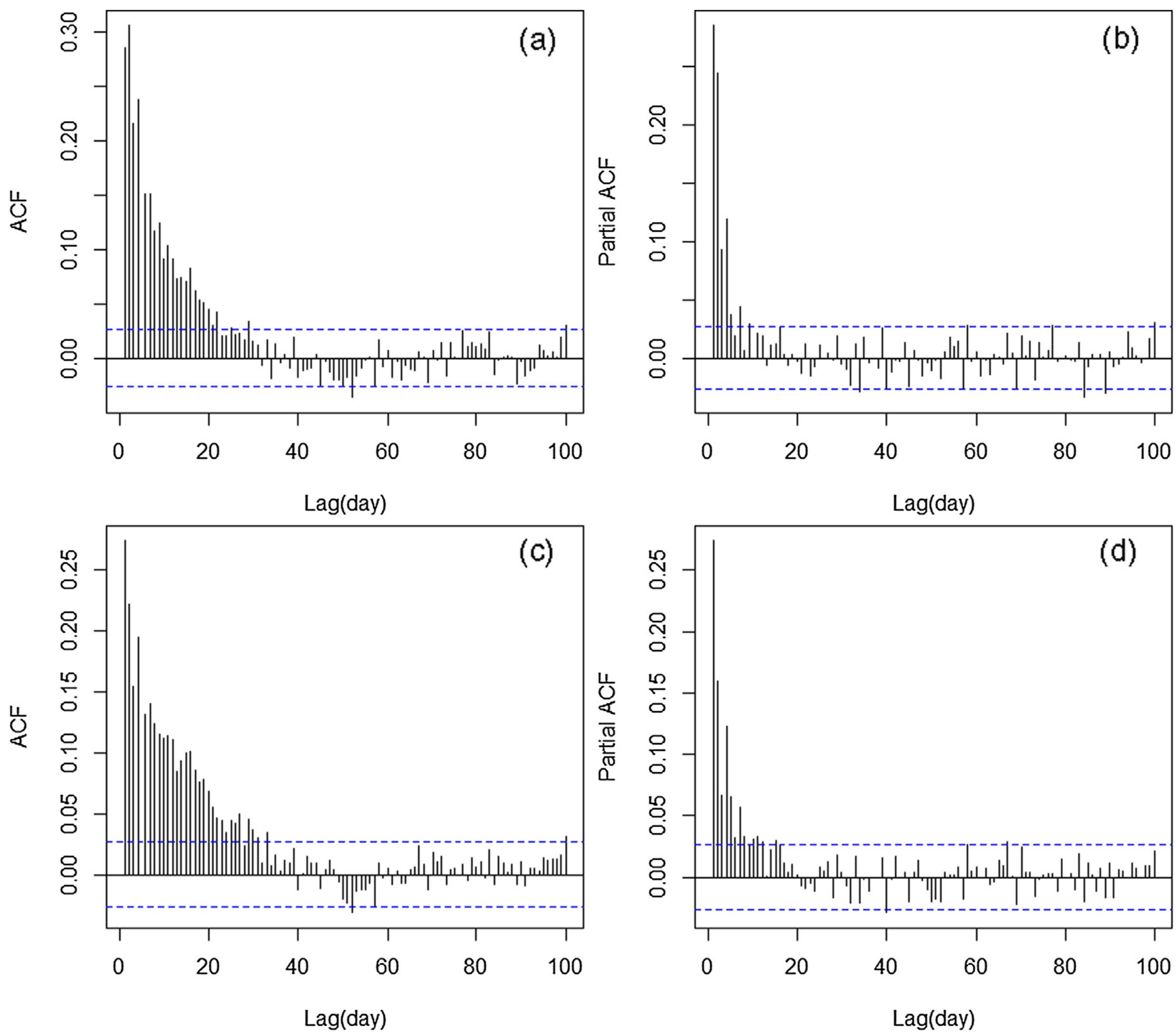

Fig. 13. (a) and (c) ACF, (b) and (d) PACF structures of the non-squared seasonally standardized residuals from the SETAR(2;4,5) and SETAR(3;5,1,3) models, respectively, for daily streamflows at "GH" station.

the mean behavior in the daily standardized residuals. Then, a GARCH model is fitted to the residuals from this additional ARMA model to address the volatility in the ARMA model. According to Fig. 13, an additional ARMA(5,1) was the most appropriate model fitted to the daily standardized residuals from the two- and three-regime SETAR models based on the AIC. The ACF structure plots of the second-residual series and its squared series from the hybrid SETAR(2;4,5)-ARMA(5,1) and SETAR(3;5,1,3)-ARMA(5,1) models are developed and depicted in Fig. 14. The meaning of the second-residual series is the residual series obtained from the additional ARMA model as a second model fitted to the daily standardized residuals from the two SETAR models. According to Fig. 14a and c, there is no autocorrelation structure in the second-residual series, but a significant autocorrelation structure exists in the squared second-residual series, as shown in Fig. 14b and d, which indicates an ARCH effect in the second-residuals. Therefore, based on the ACF and PACF structures of the squared second-residual series and the AIC value, an ARCH(5) model was fitted to the second-residual series at "GH" station. Finally, the hybrid SETAR(2;4,5)-ARMA(5,1)-ARCH(5) model for the two-regime case and SETAR(3;5,1,3)-ARMA(5,1)-ARCH (5) model for the three-regime case were fitted to daily streamflow series at "GH" station. This includes a SETAR(2;4,5) model and a SETAR (3;5,1,3) model fitted to standardized daily time series, an ARMA(5,1) model fitted to the seasonally standardized residual series obtained from the two- and three-regime SETAR models, and an ARCH(5) model fitted to the second-residual time series obtained from the ARMA(5,1) model. Such a model building process of the hybrid SETAR-ARMA-GARCH model is carried out for all other stations.

Fig. 15 shows the ACFs structure of standardized second-residual series e_t, and the squared standardized second-residual series obtained from the ARCH(5) model of hybrid SETAR(2;4,5)-ARMA(5,1)-ARCH(5) and SETAR(3;5,1,3)-ARMA(5,1)-ARCH(5) models. The results show that the significant autocorrelation structures have been basically eliminated in the non-squared and squared second-residuals in comparison to Fig. 12. Furthermore, the McLeod-Li test confirms that the ARCH(5) model, as illustrated for the "GH" station, provides a good fit to the second-residual series (Fig. 16). At this point, all *p*-values are noted to be greater than the critical level (5% significance level) and the null hypothesis of no ARCH effect is accepted for the newly created hybrid two- and three-regime SETAR-ARMA-ARCH models. Table 3 shows also the results of the fitted nonlinear two- and three-regime SETAR models and their combination with the ARCH approach for all daily streamflow time series at 6 hydrometric stations located in the study area.

4.4. Evaluation of fitted SETAR and SETAR-ARCH models

In this section, we discuss the performance of the two- and three-regime SETAR and hybrid SETAR-ARCH models fitted to daily streamflow time series by applying the evaluation criteria as discussed in the Methods section. Before illustrating the evaluation criteria, we

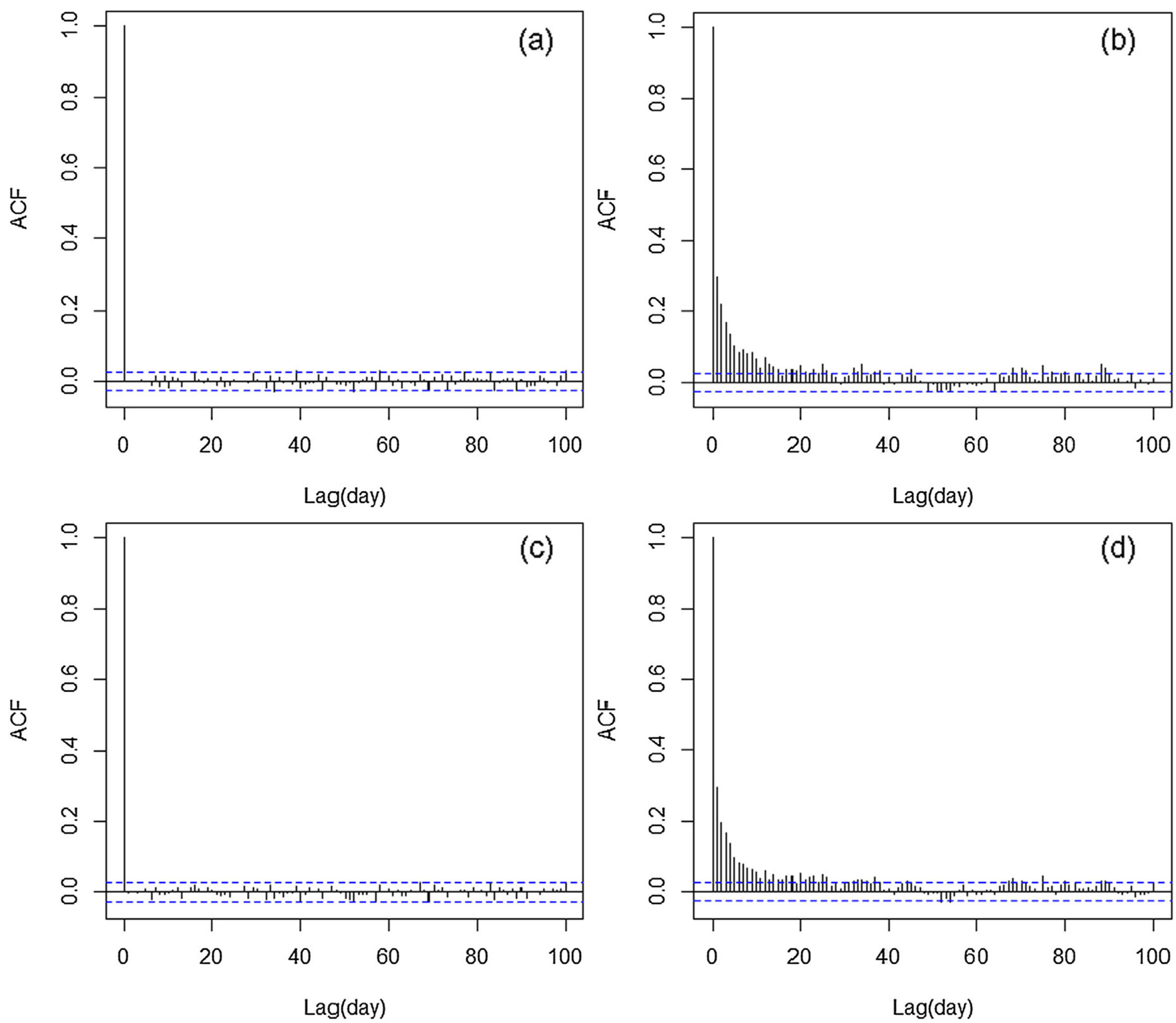

Fig. 14. ACF structure of (a) and (c) the second-residual series, (b) and (d) the squared second-residual series from the hybrid SETAR(2;4,5)-ARMA(5,1) and the hybrid SETAR(3;5,1,3)-ARMA(5,1) models, respectively, at "GH" station.

first show the scatter plots and time series plots of the observed against estimated streamflow series at "GH" station in Figs. 17 and 18, respectively. Fig. 17 indicates that the SETAR-ARCH models are better than the SETAR models in estimating high streamflows, whereas the performance of all models is good for the estimation of low streamflows. The analysis of high flows shows that the performance of the SETAR-ARCH models is slightly better than the simple SETAR models. According to the results of Amiri (2015), none of the models are able to adequately capture the high flow dynamics of the streamflows. Another indication that the SETAR-ARCH models lead to a better performance is provided by the distribution of observations around the best fit line. This distribution is the closest for the SETAR-ARCH models. The time series plots of the observed and estimated streamflows at "GH" and "D" stations are illustrated in Fig. 18 and further confirm the above explanations.

The numerical evaluation criteria are also applied and presented in Table 4 to compare the performance of the fitted two- and three-regime SETAR and SETAR-ARCH models for all stations (see Table 3). The SETAR-ARCH models show a better performance than the SETAR models based on the evaluation criteria. The performances of the hybrid models improved as shown by the RMSE and R^2 (87–92 percent) for each station. Furthermore, AME and PDIFF values indicate that the two-regime SETAR-ARCH models are more efficient in estimating the peak flows than the three-regime SETAR-ARCH models. Therefore, the combined SETAR models with ARCH, based on the model efficiency classification given by Dawson et al. (2007), can be considered as "good" to "very satisfactory". In a comparative study of the SETAR model for daily river flow forecasting, Amiri (2015) showed that the SETAR model performs better than other TAR models including the ARMA linear model and presents the best forecasting performance. These results are consistent with those of Astatkie (2006) and Komorník et al., (2006). The comparative assessment of the results of this study with soft computing methods, as applied by Wang et al., (2006), Ouachani et al., (2011), and Wang et al. (2017a,b), requires further research to understand the performance of the data-driven models.

Figs. 17 and 18 confirm that the general agreement between observed and estimated high streamflows is better in the two-regime SETAR-ARCH model than the three-regime model. The main advantage of the ARCH model is the capacity to capture the conditional heteroscedastic variances from the residual series of nonlinear SETAR models. Furthermore, the reduction of the variation of the model output as well as the reduction of the uncertainty of model estimation confirms the advantages of the GARCH approach. The results of this study are in line with the results of Chen et al. (2008) and Modarres and Ouarda (2013c) which modelled conditional heteroscedasticity for daily streamflow time series using different types of GARCH models. Romilly (2005) confirmed that the GARCH model is able to capture the heteroscedasticity to present the better performance of the model in the case of temperature time series.

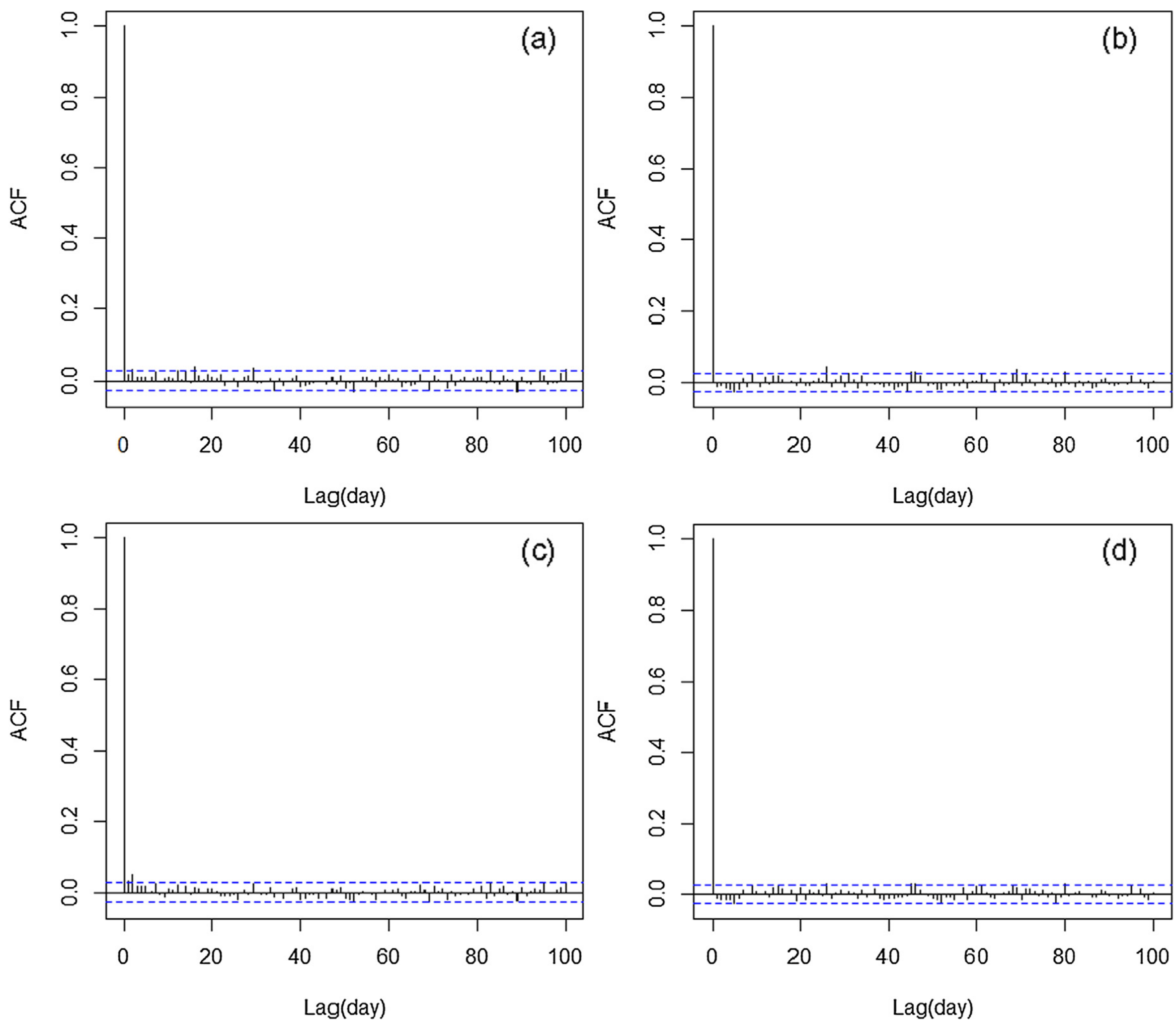

Fig. 15. ACF structure of (a) and (c) the standardized second-residual series, (b) and (d) the squared standardized second-residual series from the hybrid SETAR (2;4,5)-ARMA(5,1)-ARCH(5) and the hybrid SETAR(3;5,1,3)-ARMA(5,1)-ARCH(5) models, respectively, at “GH” station.

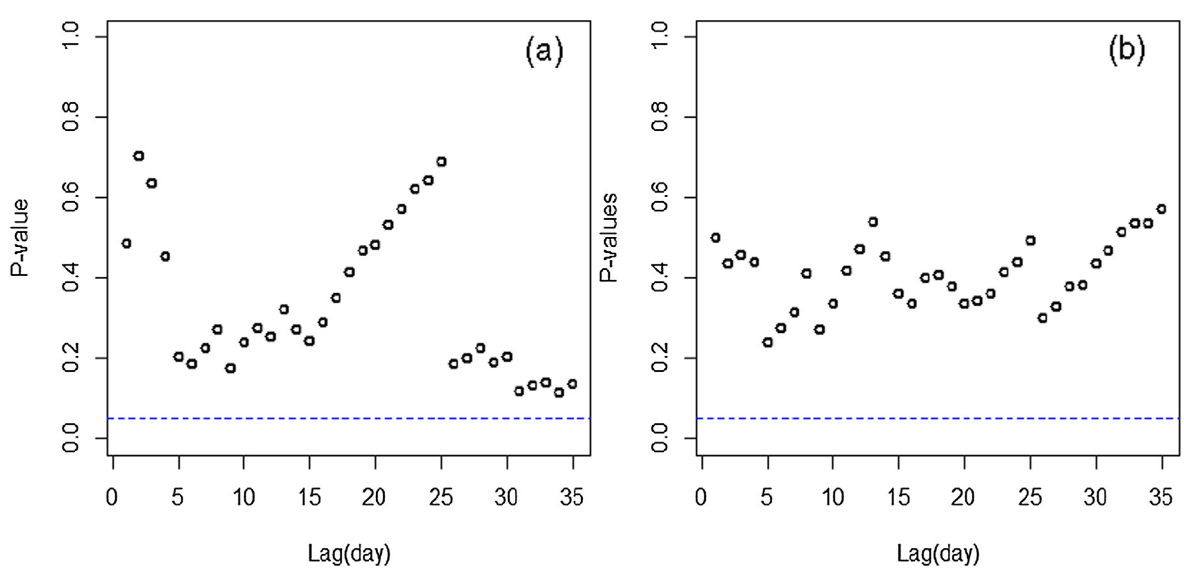

Fig. 16. *p*-values of the McLeod-Li test for the standardized second-residual series from (a) the hybrid SETAR(2;4,5)-ARMA(5,1)-ARCH(5) model and (b) the hybrid SETAR(3;5,1,3)-ARMA(5,1)-ARCH(5) model.

Table 3
Results of the fitted two- and three-regime SETAR models and their combination with GARCH approach for daily streamflow series in the study area.

Station names	Model number	Nonlinear SETAR models	Model number	Nonlinear SETAR-GARCH models
"GH"	1	SETAR(2;4,5)	2	SETAR(2;4,5)-ARMA(5,1)-ARCH(5)
	3	SETAR(3;5,1,3)	4	SETAR(3;5,1,3)-ARMA(5,1)-ARCH(5)
"D"	1	SETAR(2;4,10)	2	SETAR(2;4,10)-ARMA(4,1)-ARCH(13)
	3	SETAR(3;2,1,8)	4	SETAR(3;2,1,8)-ARMA(8,1)-ARCH(13)
"PG"	1	SETAR(2;4,8)	2	SETAR(2;4,8)-ARMA(4,1)-ARCH(8)
	3	SETAR(3;2,3,8)	4	SETAR(3;2,3,8)-ARMA(8,1)-ARCH(7)
"PA"	1	SETAR(2;2,10)	2	SETAR(2;2,10)-ARMA(7,1)-ARCH(10)
	3	SETAR(3;4,1,8)	4	SETAR(3;4,1,8)-ARMA(5,1)-ARCH(8)
"S"	1	SETAR(2;4,15)	2	SETAR(2;4,15)-ARMA(12,0)-ARCH(9)
	3	SETAR(3;3,3,15)	4	SETAR(3;3,3,15)-ARMA(14,1)-ARCH(9)
"SK"	1	SETAR(2;4,8)	2	SETAR(2;4,8)-ARMA(3,1)-ARCH(6)
	3	SETAR(3;2,3,4)	4	SETAR(3;2,3,4)-ARMA(11,1)-ARCH(5)

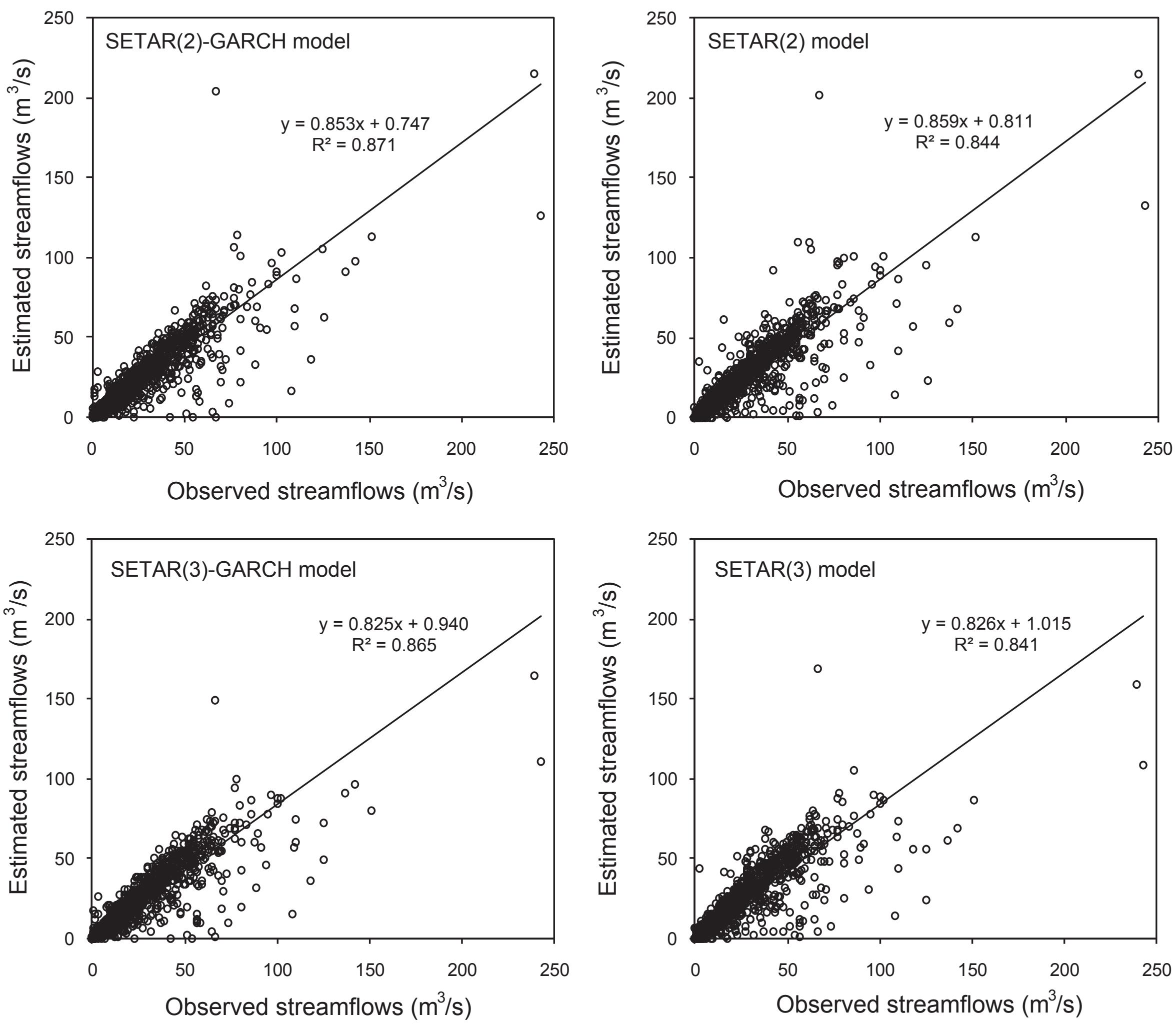

Fig. 17. Scatter plots of the observed against estimated daily streamflows for the two- and three-regime SETAR and SETAR-GARCH models at "GH" station.

5. Conclusions

The objective of the present study is to model the daily streamflows of the Zarrineh Rood Basin Rivers located in the south of Lake Urmia by applying two- and three-regime SETAR models and their combination with the ARCH approach. Relatively little attention has been paid to these two approaches in hydrology and water resources engineering. The proposed approaches are applied to six streamflow time series and their performances are evaluated using various criteria. The results can be summarized as follows:

The hybrid SETAR-ARCH models consist of two parts; the first part considers the two- and three-regime SETAR models for modeling the mean behavior (conditional mean) of streamflow series, the second part considers the ARCH approach for modeling the variance behavior (conditional heteroscedasticity) of the residual series gained from the SETAR models. The evaluation criteria show that the SETAR-ARCH models lead to better performances when compared with the SETAR models. Moreover, the performance of the two-regime SETAR model is slightly better than the performance of the three-regime SETAR one. Hybrid SETAR models are shown to improve over classical models and can be appropriate for modeling and analyzing streamflows.

The results of the McLeod-Li test show the existence of conditional

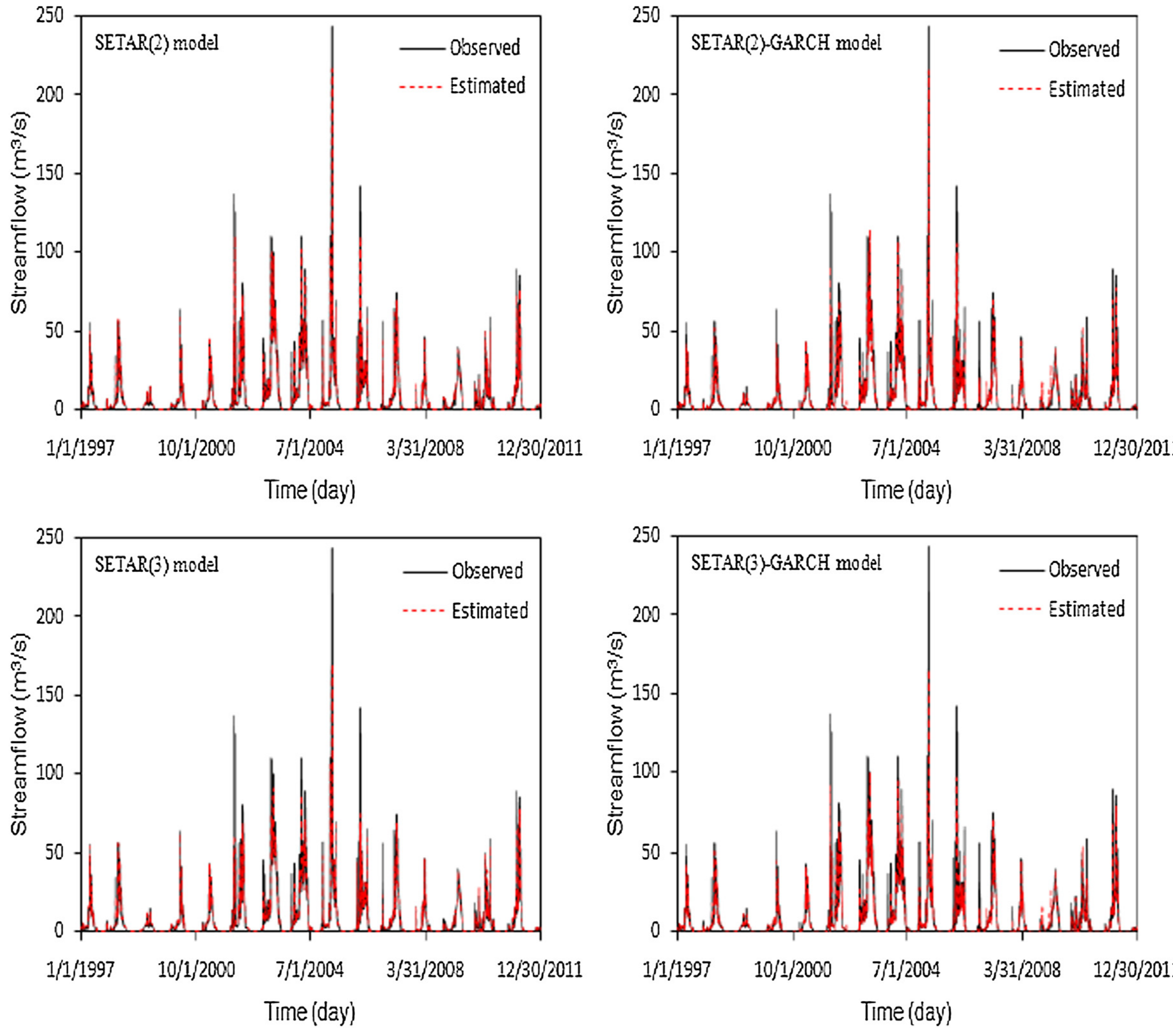

Fig. 18. Time series plot of the observed and estimated daily streamflows for the two- and three-regime SETAR and SETAR-GARCH models at "GH" station.

Table 4
Evaluation criteria of the fitted SETAR and GARCH models to daily streamflow time series in the study area.

Station names	Model number	AME (m^3/s)	PDIFF (m^3/s)	MAE (m^3/s)	RMSE (m^3/s)	RAE	R^2
"GH"	1	135.30	27.44	1.50	5.93	0.16	0.84
	2	137.10	27.74	1.41	5.41	0.15	0.87
	3	133.91	73.96	1.54	6.00	0.17	0.84
	4	132.40	77.90	1.47	5.56	0.16	0.86
"D"	1	109.36	11.19	1.30	5.27	0.15	0.86
	2	86.62	13.29	1.24	4.70	0.14	0.89
	3	108.13	19.87	1.30	5.30	0.15	0.86
	4	86.32	21.18	1.23	4.65	0.13	0.89
"PG"	1	145.43	25.96	1.92	7.60	0.15	0.90
	2	158.42	9.00	1.80	6.97	0.14	0.90
	3	144.81	27.00	1.92	7.6	0.15	0.88
	4	155.10	13.33	1.80	6.89	0.14	0.90
"PA"	1	165.36	22.4	2.24	8.54	0.16	0.88
	2	143.70	10.67	2.06	7.57	0.15	0.90
	3	165.08	26.44	2.23	8.54	0.16	0.88
	4	145.69	20.71	2.08	7.66	0.14	0.90
"S"	1	171.78	32.94	1.27	6.08	0.14	0.86
	2	184.96	31.00	1.22	5.67	0.13	0.88
	3	169.00	34.04	1.28	6.06	0.14	0.86
	4	189.33	40.89	1.23	5.78	0.13	0.87
"SK"	1	72.83	11.53	0.97	3.88	0.13	0.92
	2	77.85	39.5	0.92	3.76	0.12	0.92
	3	72.68	18.91	0.96	3.86	0.13	0.92
	4	77.6	43.6	0.92	3.76	0.12	0.92

heteroscedasticity in the residual series from SETAR models. According to the performance evaluation of the fitted models, it is possible to conclude that the hybrid SETAR-ARCH models improve over the SETAR models without ARCH approach, and their outputs can be considered as "very satisfactory". The results of this research have direct applications whenever it is important to capture the heteroscedasticity in the residuals of the nonlinear threshold time series.

Future research efforts should attempt to apply the ARCH modeling approach and the SETAR models and their combination with soft computing methods to streamflow time series from different parts of the world. The application of nonlinear multivariate time series regression models with exogenous data, such as climate variables, for modeling streamflows is also proposed for future efforts. The application of multivariate ARCH models for modeling the effects of climate variability and change on streamflow fluctuations is also an interesting topic for future research. Few studied have applied either nonlinear SETAR and GARCH models or their combinations. Future work can focus on the application of these models to other hydrologic and climatic variables at different time scales using different types of TAR and GARCH models.

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