Stoch Environ Res Risk Assess (2009) 23:1063–1070
DOI 10.1007/s00477-008-0277-8

ORIGINAL PAPER

Streamflow drought time series forecasting: a case study in a small watershed in North West Spain

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Published online: 2 October 2008
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Abstract Drought is a climatic event that can cause significant damage both in natural environment and in human lives. Drought forecasting is an important issue in water resource planning. Due to the stochastic behaviour of droughts, a multiplicative seasonal autoregressive integrated moving average model was applied to forecast monthly streamflow in a small watershed in Galicia (NW Spain). A better streamflow forecast obtained when the Martone index was included in the model as explanatory variable. After forecasting 12 leading month streamflow, three drought thresholds: streamflow mean, monthly streamflow mean and standardized streamflow index were chosen. Both observed and forecasted streamflow showed no drought evidence in this basin.

Keywords Streamwater · Drought · Forecasting · Time series · Caldas catchment

1 Introduction

Streamflow is a key hydrological process that summarizes various atmospheric, land surface and subsurface components of the hydrologic cycle (Pielke et al. 2005). In Spain, as in other countries, the availability of water for different uses from forested watersheds is a subject of concern. However, available long-term hydrological information, at watershed level, is still scarce in NW Spain (Gras 1992, 1993; Gras et al. 1993; Fernández et al. 2006).

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Projections for the current century from global change scenarios predict a decrease in annual precipitation in NW Spain of between 10 and 15% (De Castro et al. 2005). Iglesias et al. (2005) argue that this probable decrease in rainfall will affect runoff with a predicted reduction in water resources of about 20% in subsequent years. Long-term management must consider the potential effects of climate change on seasonal variability, and on extreme and mean values of hydrological processes. As pointed out by Ma and Fu (2003), the decrease in precipitation is not a drought signal due to the uncertainity of evaporation. Although the definition of drought is not clear, it is commonly classified as meteorological, hydrological and agricultural droughts, and many drought indices used for assessing drought severity (Keyantash and Dracup 2002). In this study, we used monthly streamflow to evaluate the existence or not of drought in a small forested watershed. As yet there is no such information available for the north west of the Iberian Peninsula.

Several studies have developed methods of analysing stochastic characteristics of hydrologic variables (e.g. Chung and Salas 2000; Kim and Valdes 2003; Mishra and Desai 2005) and particularly streamflow (Panu et al. 1978; Govindaswamy 1991; Yürekli et al. 2005; Modarres 2007) for drought forecasting. During the past decades, several studies have developed methods of analysing stochastic characteristics of hydrologic time series. The most widely used model is the ARIMA model.

The ARIMA models seem to offer a potential to develop reliable forecasts towards prediction of drought duration and severity (Mishra and Desai 2005; Modarres 2007). The ARIMA model approach has several advantages over other methods, in particular, its forecasting capability, its richer information on time-related changes, or the consideration of serial correlation between observations. Also, few parameters are required for describing time series, which exhibit non-stationarity both within and across the seasons.

The aim of this study was to develop a stochastic model to forecast streamflow drought in a small forested watershed. The importance of considering the selected study-area is because of the basin is covered by a forestry species very important for the economy of the region and no study was conducted earlier for drought analysis in this area.

2 Materials and methods

2.1 Study area

The experimental area is located 20 km north of Pontevedra (42°34′28″–42°34′48″N and 8°36′57″–8°37′08″W; Fig. 1). It is a small watershed (6.7 ha) covered by a *Pinus pinaster* Ait. plantation. This watershed is part of the experimental basins network of the Environmental Research Centre (Xunta de Galicia). Mean altitude is 200 m. Soils are Humic Umbrisols, and Alumiumbric Regosols (Calvo de Anta and Macías 2001), sandy and sandy–loam textured and developed on granitic or granodiorite parent material. Climate is temperate and rainy. Mean annual temperature is 14°C. Mean temperature is 9°C in the coldest month and 20.5°C in the hottest month. Average annual precipitation is 1,700 mm/year and 41% of this amount falls in the period October–December. There is a dry period in summer (July–September), when 12% of the annual precipitation falls.

A small river is contributing the flow in Caldas catchment. The water is primarily used for *P. pinaster* cultivation, an important economic resource in the area. It is representative of these kind of plantations in the region where most of the water demand for forest growth is supplied by these small rivers.

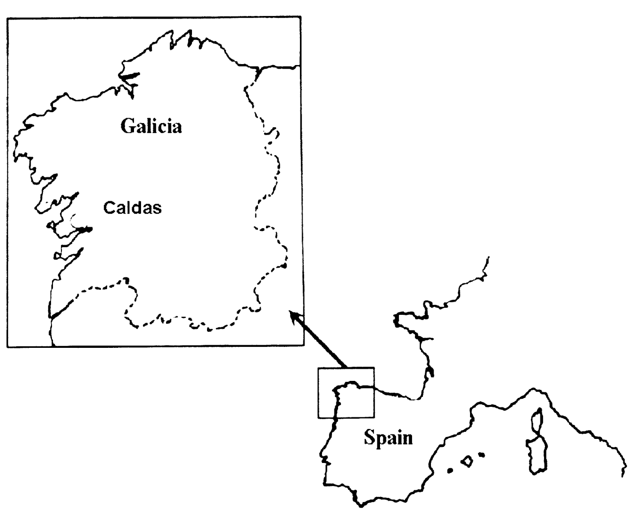

Fig. 1 Location of study-site

Table 1 Summary of monthly and annual parameters in the Caldas watershed during the period 1988–2006

Months	Streamflow (mm)	Precipitation (mm)	Martonne index
January	116.1 (24.1)	204.7 (29.8)	10.5 (1.4)
February	60.0 (9.5)	124.1 (17.1)	6.2 (0.9)
March	57.4 (13.2)	124.8 (27.1)	5.8 (1.3)
April	43.9 (6.2)	147.9 (24.7)	6.1 (0.9)
May	37.0 (5.3)	124.8 (18.5)	4.7 (0.7)
June	25.7 (3.1)	48.6 (7.9)	1.7 (0.3)
July	12.2 (1.9)	43.3 (10.2)	1.4 (0.3)
August	6.2 (0.7)	52.6 (12.4)	1.7 (0.4)
September	5.4 (0.7)	85.9 (15.6)	3.2 (0.5)
October	11.8 (2.3)	238.9 (24.2)	11.1 (1.5)
November	44.9 (12.5)	259.7 (37.4)	13.9 (2.3)
December	80.3 (23.4)	206.5 (34.4)	11.0 (1.8)
Annual mean	41.74 (13.64)	138.48 (28.37)	6.43 (1.51)

The standard error is shown in brackets

2.2 Data collection

Mean precipitation data were obtained as an arithmetic mean from a network of carefully located rainfall gauges in the watershed. Streamflow was continuously measured at the outlet of the catchment with a 90° V-notch weir with standard ink scripture limnigraphs (OTT Kempten). Charts were digitized and runoff calculated according to the weir shape. The mean values of the hydrologic parameters in the Caldas catchment are shown in Table 1.

2.3 Statistical analysis

A time series approach was used to model monthly streamflow and to identify relationships between the environmental variables and streamflow because of the serial dependence of the data over time. Because of this autocorrelation, observations over time are not independent and therefore correlations with observations of environmental data at various times violate the assumptions of regression analysis.

The Box and Jenkins (1976) modelling approach was used. ARIMA (p, q, d) models can have an autoregressive term (AR) of order p, a differencing term (I) of order d, and a moving average term of order q. The general non-seasonal ARIMA model may be written as

$$\phi(B)(1-B)^d Y_t = \theta(B)a_t$$

where Y_t is the observed series, B is the backshift operator; that is $BX_t = X_{t-1}$, $\phi(B)$ is the autoregressive operator, represented as a polynomial in the backshift operator of order p: $\phi(B) = 1 - \phi_1(B) - \cdots - \phi_p(B)^p \theta(B)$ is the moving-average operator, represented as a polynomial in the backshift operator of order q: $\theta(B) = 1 - \theta_1 B - \cdots - \theta_q B^q a_t$, the random error.

For seasonal time series that contain cyclic features, the multiplicative seasonal ARIMA is expressed as (p, d, q) (P, D, Q) s where p is the order of non-seasonal autoregression, d, the number of regular differencing, q the order of non-seasonal MA, P the order of seasonal autoregression, D, the number of seasonal differencing, Q the order of seasonal MA, s the length of the season.

The seasonal ARIMA model is written as

$$\phi_p(B)\Phi_P(B^s)(1-B)^d(1-B^s)^D Y_t = \theta_q(B)\Theta_Q(B^s)a_t$$

Determination of the order of each term in the model is made by examination of the raw data and plots of the autocorrelation function (ACF) of the data. In ARIMA models it is assumed that the series being modelled is stationary (the series exhibit the same mean level and variance in time). Appropriate differencing of the series or logarithm transformation is performed (if required) to achieve stationarity in mean and variance, respectively.

The Akaike's Information Criterion (Akaike 1974) was used for model selection. The statistic is used to evaluate the goodness of fit with smaller values indicating a better fitting and more parsimonious model than larger values.

After model identification, parameter estimates must be obtained. These parameters should satisfy the conditions of stationarity and invertibility for autoregressive and moving average models, respectively (Box and Jenkins 1976; Salas et al. 1980). We used maximum likelihood to estimate the model parameters. ARIMA models can incorporate many series of independent variables. The general form of a dynamic regression is

$$P(B)Y_t = \beta X_t + a_t$$

where $P(B)$ is the polynomial in the backshift operator as those explained in the ARIMA model, β correlation coefficient of the independent variables (X_t) and a_t, the random error.

Chen et al. (2007) stated that the variation in runoff is the result of the combined effect of precipitation and temperature, so we assume that the variables precipitation and Martonne index influenced streamflow. The Martonne index is the ratio between the monthly precipitation (P) and the mean values of temperature (T) plus 10°C (Martonne 1973). We used plots of cross-correlation coefficients to identify relationships between the explanatory and dependent variables.

The remaining residual series should have characteristics of random error. Time independence of the residuals was checked with the Portmanteau lack of fit test (Salas et al. 1980). Normality and homoscedasticity of residuals were tested with the Kolmogorov–Smirnov and Breusch–Pagan tests, respectively (Yürekli et al. 2005).

2.3.1 *Model calibration*

In order to evaluate the accuracy of the streamflow forecast, the following tests were used:

- Correlation between observed and forecasted series.
- Coefficient of efficiency (Brath and Rosso 1993)

$$E = 1 - \Sigma\left(Q_t - Q_t^*\right)^2 / \Sigma(Q_t - Q_m)^2$$

where Q_t^* is the discharge forecasted, Q_t is the corresponding observed streamflow and Q_m is the mean of the whole series of the observed streamflow.

- The root mean squared errors for forecasted streamflow.

$$\text{RMSE} = \Sigma((F_i - O_i)/n)^{1/2}$$

where F_i and O_i are forecasted and observed streamflow.

- The Wilcoxon rank sum method for the difference between forecasted and observed streamflow means.
- Non-parametric test for the quality of observed and forecasted streamflow variances (Levene 1960).

Model computation was made with streamflow monthly data from between January 1988 and December 2006. The period January and December 2007 was considered in forecasting estimations of the model.

We used two additional periods for forecasting to test the validity of the model for forecasting. In the first period the model was used to forecast monthly streamflow for the period January 2003 to December 2007. In the second, for the period January 2005 and December 2007.

The SPSS (2004) statistical package was used for carrying out the analysis.

2.4 Drought definitions and thresholds

A drought was defined by Yevjevich (1967) as an uninterrupted sequence of streamflow below an arbitrary level. The mean value of the streamflow time series during the study-period was selected as the truncation level; the monthly mean values were also applied as the second truncation level for each month (Modarres 2007).

As defined by Modarres (2007) we used the standardized streamflow index (SSFI) as a drought index. This index is statistically similar to the SPI defined by McKee et al. (1993) for meteorological drought analysis. The SSFI for a given period is defined as the difference between streamflow from mean divided to standard deviation (Modarres 2007). Weather classification based on SPI is shown in Table 2.

Table 2 Weather classification based on SPI

Values	Class
>2.0	Extremely wet
1.55–1.99	Very wet
1.0–1.49	Moderately wet
−0.99 to 0.99	Near normal
−1 to −1.49	Moderately dry
−1.5 to −1.99	Severely dry
>−2.0	Extremely dry

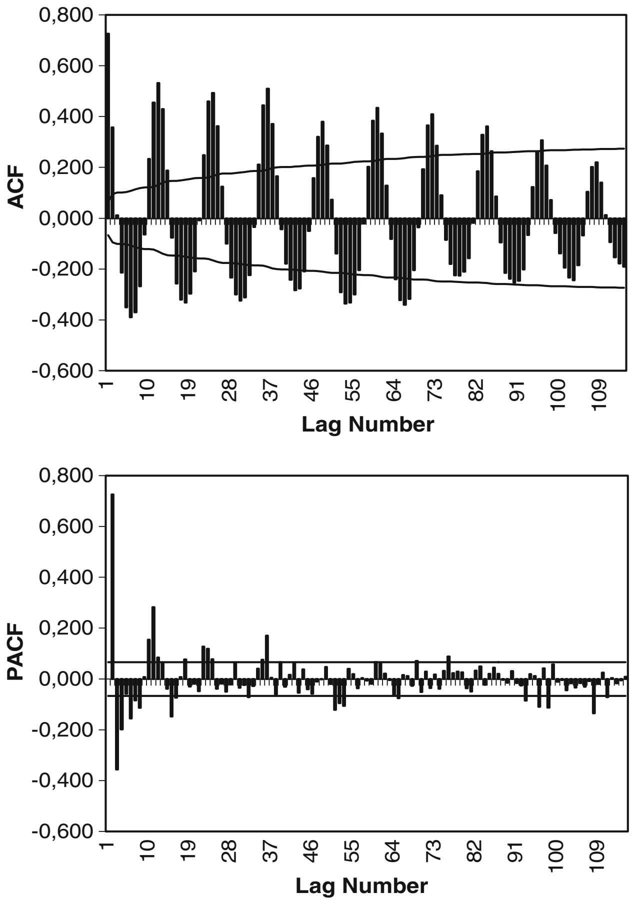

Fig. 2 Autocorrelation function (*ACF*) and partial autocorrelation function (*PACF*) plots of non-seasonal differenced time series

3 Results and discussion

In the first step of model identification, the data was found to be non-normally distributed (Kolmogorov–Smirnov statistic, $D = 0.242$), and therefore a logarithmic transformation was applied. The Kolmogorov–Smirnov (K-S) test of normality was also done for the transformed series and the null hypothesis of normality is accepted at 5% level as the K-S statistic, $D = 0.031$ is smaller than the critical value (0.200). The ACF curve (Fig. 2) decayed with mixture of sine and exponential curve and in partial autocorrelation function (PACF) there was a significant lag at 1, which suggests an AR process. In the PACF there were significant spikes present near lag 12, 24 and 36, and therefore the series was seasonally differenced with 12 as the period. The plot of ACF and PACF after seasonal differenciation is shown in Fig. 3. In the PACF there was a significant spike at lag 1, which indicates an AR (1) as non-seasonal part of the model. The identification of best model for streamflow series based on minimum AIC is shown in Table 3. The model finally selected was an ARIMA (1,0,0) $(2,1,0)_{12}$. The

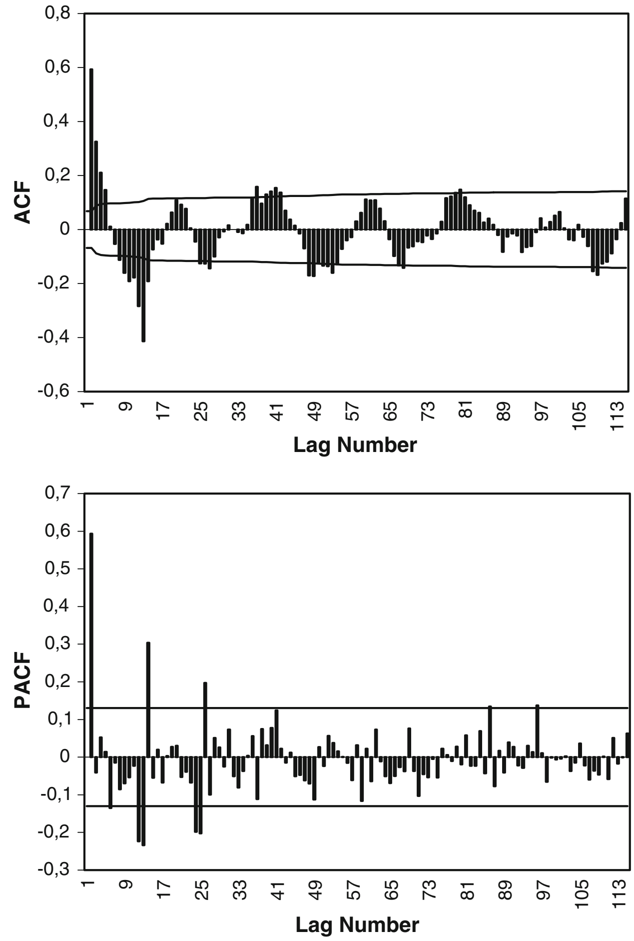

Fig. 3 Autocorrelation function (*ACF*) and partial autocorrelation function (*PACF*) plots of seasonal differenced time series

Table 3 Comparison of AIC for selected candidate models

Model	AIC
ARIMA (1,0,0) (2,1,0)12	466.089
ARIMA (1,1,0) (2,1,0)12	499.294
ARIMA (2,0,0) (2,1,0)12	468.037
ARIMA (2,1,0) (2,1,0)12	499.643

Table 4 Results of parameter estimation for the selected model

Model	AIC	Parameters	Values	Standard error	*t*-Ratio	$P < 0.05$
Model 1	466.089	$\phi1$	0.630	0.054	11.663	0.000
		$\Phi1$	−0.706	0.063	−11.261	0.000
		$\Phi2$	−0.455	0.061	−7.448	0.000

statistical analysis of model parameters is shown in Table 4. The model equation is as follows:

$$(1-0.63B)\left(1+0.71B^{12}+0.46B^{24}\right)\left(1-B^{12}\right)Y_t=a_t$$

The results of the Porte Manteau lack-of-fit test indicate that the residuals of this model are independent ($Q_r = 48.76$ lower than the critical value 63.98). The normality and heteroscedasticity tests statistics are 0.148 (<0.200 critical value) and 0.60 (<1.46 critical value), respectively, which confirm normality and homogeneity of the residuals. The comparison between observed and forecasted streamflow series can be seen in Fig. 4.

The comparison between forecasting periods (Table 5), showed that the scenarios 2 (2005–2007) and 3 (2007) are suitable for streamflow forecasting. However, higher correlation and efficiency coefficient were obtained in the scenario 3 in which 1-year monthly streamflow has been forecasted. This indicates that the model is suitable for forecasting for 12 months ahead which was the objective of this study.

We also considered including some independent variables in the ARIMA model to improve the streamflow forecast. The variables used were monthly precipitation and monthly values of the Martone index (Martonne 1973). The mean values of these parameters during the study period are listed in Table 1. The lowest AIC was obtained for the model 3 (Table 6). In all cases, residuals were time-independent, homoscedastic and normally distributed (Table 7) as the values of the three statistics were lower

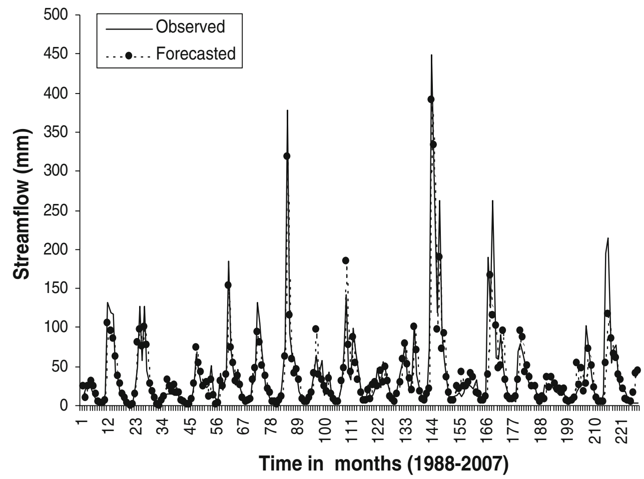

Fig. 4 Comparison of observed data with predicted data using the ARIMA model

Table 5 Test results for the comparison between forecasted and observed series using different forecasting scenarios (95% confidence level)

Forecasting scenario	Correlation coefficient	Coefficient of efficiency	RMSE	Wilcoxon's *P* value	Levene's *P* value
Scenario 1 (2003–2007)	0.51	0.350	3.10	0.034	0.027
Scenario 2 (2005–2007)	0.60	0.578	2.92	0.096	0.057
Scenario 3 (2007)	0.80	0.920	2.34	0.388	0.778

Table 6 Results of parameter estimation for the selected model including explanatory variables

Model	AIC	Parameters	Values	Standard error	*t*-Ratio	$P < 0.05$
Model 2	404.452	$\phi1$	0.613	0.052	11.792	0.000
		$\Phi1$	−0.679	0.066	−10.299	0.000
		$\Phi2$	−0.370	0.065	−5.690	0.000
		Precipitation	0.003	0.000	8.669	0.000
Model 3	402.484	$\phi1$	0.612	0.052	11.734	0.000
		$\Phi1$	−0.687	0.066	−10.370	0.000
		$\Phi2$	−0.349	0.065	−5.323	0.000
		Martonne index	0.062	0.007	8.915	0.000

Table 7 Time independence and normality of residuals tests for the selected model including explanatory variables

Model	Kolmogorov–Smirnov statistic	Critical value	Breusch–Pagan statistic	Critical value	Portmanteau Q statistic	Critical value
Model 2	0.120	0.200	0.46	1.46	42.88	63.98
Model 3	0.130	0.200	0.52	1.46	3.72	63.98

Table 8 Test results for the comparison between observed and forecasted series at 95% confidence level

	Correlation coefficient	Coefficient of efficiency	RMSE	Wilcoxon's P value	Levene's P value
Model 2	0.94	0.994	1.22	0.695	0.790
Model 3	0.94	0.999	0.54	1.000	0.989

than the respective critical values. The results of the model calibration (Table 8) showed that the models are appropriate for streamflow forecast, although the best adjustments were shown by the model that included the Martone index.

$$(1-0.61B)\left(1+0.69B^{12}+0.35B^{24}\right)\left(1-B^{12}\right)Y_t = 0.06 \text{ Martonne index}_t + a_t$$

This result appeared to indicate the indirect influence of monthly precipitation and temperature on water yield in this small watershed. Precipitation was observed to have a significant effect on water yield after perturbations in a small *Eucalyptus globulus* Labill. catchment in this area (Fernández et al. 2006). Chen et al. (2007) also stated the influence of temperature and precipitation on streamflow trends.

Observed and forecasted values from the first (Fig. 5a) and third model (Fig. 5b) were used to identify a drought period during 2007. The comparison between observed and forecasted streamflow with these models and the truncation levels (annual and monthly streamflow means) chosen for drought forecasting revealed that there was no significant drought in 2007 (Fig. 5). However, a trend towards a drier winter was apparent. Zheng et al. (2006) also detected a reduction in streamflow in winter in the Yellow River in China whereas changes in the annual streamflow were less apparent.

Following the SPI drought severity classification (Table 2) the comparison between observed and forecasted SSFI (Table 9) also showed that there is no appreciable drought in the study area.

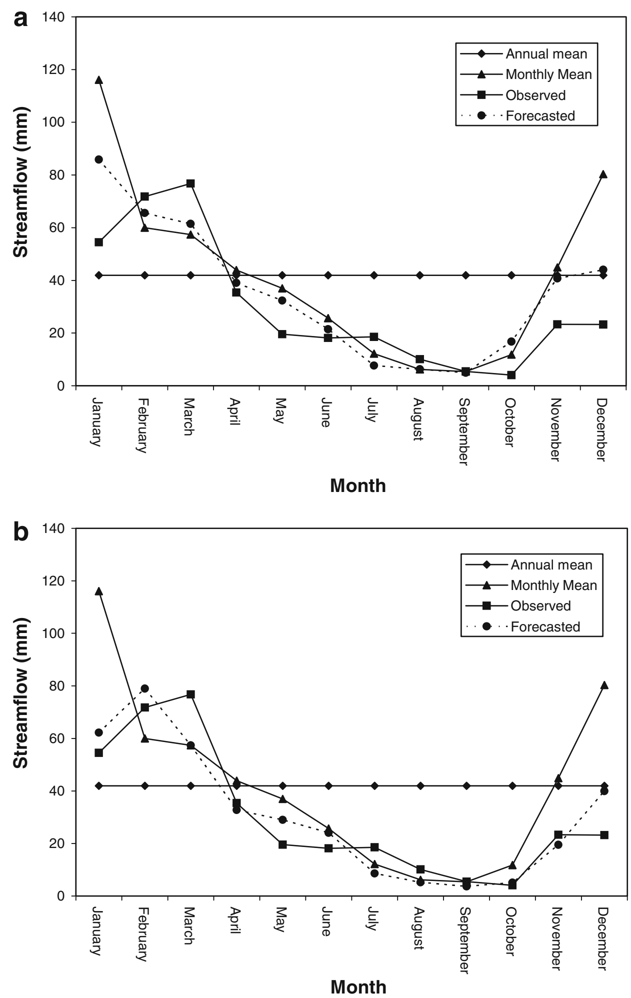

Fig. 5 Comparison of observed and forecasted streamflow from model 1 (**a**) and 3 (**b**) and two drought truncation levels

4 Conclusions

We can conclude that the model is valid for forecasting of monthly streamflow. Adding explanatory variables to the ARIMA models could enhance the accuracy of the model for streamflow forecasting. The proposed explanatory variables, precipitation or the combination between precipitation and air temperature (Martonne index), are not difficult to obtain and is feasible to be incorporated in a predictive model. No

Table 9 Observed and forecasted SSFI and their classification based on SPI

Lead-time	Forecasted SSFI model 1	Forecasted SSFI model 3	Observed SSFI	Drought classification
January	−0.36	−0.65	−0.56	Near normal
February	0.74	0.45	0.27	Near normal
March	0.24	0.37	0.33	Near normal
April	−0.40	−0.28	−0.30	Near normal
May	−0.24	−0.31	−0.29	Near normal
June	−0.37	−0.45	−0.53	Near normal
July	0.44	0.66	0.72	Near normal
August	0.43	0.48	0.55	Near normal
September	−0.57	−0.57	−0.60	Near normal
October	−0.50	−0.62	−0.70	Near normal
November	−0.49	−0.53	−0.63	Near normal
December	−0.33	−0.40	−0.49	Near normal

evidence of drought was observed in this small watershed. This result was obtained using simple thresholds (mean and monthly mean) or the normalized streamflow drought index. The incorporation of the explanatory variables in the ARIMA model will result in better predictions for drought forecasting and water resources management.

In general, it can be concluded that there is no evidence of drought conditions in the study area, although the results may be constrained by the time-span of model construction.

Acknowledgments This study was funded by the Galician Research, Science and Technology Commission, the National Institute of Agricultural Research of Spain (INIA) and the Galician Research and Development Directorate through the projects 8636, SC-93-096 and PGIDIT05RFO50202PR, respectively. This work was also co-financed by the European Social Fund (Dr. C. Fernández). We are grateful to all those who have helped with data collection, particularly José Ramón González and Antonio Arellano. We sincerely acknowledge the critical reviews of the Editor and the anonymous referees who helped improve an early version of the manuscript.

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