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Comparison of prediction performances between Box–Jenkins and Kalman filter models—Case of annual and monthly sreamflows in Algeria

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ABSTRACT

The present study aims to investigate and to compare Box–Jenkins (BJ) and Kalman filter (KF) models to predict stream flows in northern Algeria. For this purpose, annual and monthly data of 10 hydrometric stations have been considered for application. The results with BJ models led to five Autoregressive and integrated moving average (ARIMA) models for the annual streamflows, with an overall mean explained variance at 63% level, whereas for the monthly flows they led to 10 Seasonal Autoregressive and integrated moving average (SARIMA) models, with an overall mean explained variance around 75%. On the other hand, KF methodology led to two on-line operations, where multisite optimal annual and monthly predictions are obtained. The KF and BJ predictive performances are then compared via some statistical parameters of their prediction error. For both of annual and monthly scales, it is found that KF model performs better in predictions. For example, the mean prediction error for KF is 16 times smaller than the BJ models, the corresponding standard deviation, minimum and maximum values are respectively, 5, 6, and 3 times smaller than the BJ alternatives. This denotes the superiority of KF for the prediction of stream flows in northern Algeria. In addition, an eventual tendency of KF to the underestimation has also been noticed from the prediction error standard deviation illustration.

Keywords: Stream flows; ARIMA; SARIMA; Kalman filter; Prediction error

1. Introduction

In a semiarid country such as Algeria, water is an element of survival that strongly influences any social or economic development. Unfortunately, water resources are facing big challenges due to precipitation deficit and scarcity, as well as their geographical variability. It is important to notice that among the 100 billioncubic meters received in the form of precipitation per year, on the northern part of Algeria, only 4.8 billion are captured in operational dams [1]. Of course, this statistic is given without the different types of losses that make this quantity lesser, which is to cope with the increasing demand of water for agricultural, industrial, and domestic uses. According

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to Haddad and Rahla [2], water demand reached 5 billion cubic meters per year with a supply of $170 m^3$/capita/d, whereas a minimum standard of $250 m^3$/capita/d is already considered as a deficit. This problematic becomes bigger from year to year, and hence, needs some urgent and efficient solution in order to overcome the demand deficit and insure a regular supply with water to all water utilizations.

The new policy of Algeria focuses on integrated management of water resources [3], and therefore, two types of actions are to be considered; the first one is the optimal management, while the second deals with the water resources economy. In its Initial National Communication, Algeria has already projected a program of actions to deal with climate changes. In terms of water, this program integrates watershed management among other points. In addition, the program of investment and water development occupies an important place in the program (2010–2014) of the Algerian government [4]; it will be positively completed by any scientific research or technological development, which will certainly have a positive impact on water resources.

The present study is a modest contribution to the success of this new water policy. Through it, we would like to give some helpful tools for the planners. One of the advantages of the proposed tools is that the stochastic nature of the hydrological variable is taken into account, as well as its temporal and spatial variation, which is a big difficulty to overcome. The great advantage is that one of the tools provides accurately with the prediction error covariance and can deal with changes in the model parameters and variances.

The objective of this study is to investigate both of Box–Jenkins (BJ) and Kalman filter (KF) models for monthly and annual stream flow predictions. Through the comparison of the corresponding prediction errors, it is possible to determine which one is better for further predictions in the study area. In the literature, such applied research is rather rare, particularly, for Algerian data. However, Harrison and Stevens [5] showed that many forecasting methods are special cases of KF. Ahcen and O'Connor [6] argued that the minimum mean-square error forecasts are identical for KF and BJ when the flow forecasting model is assumed to be autoregressive moving average model and the corresponding flow data are free of measurement errors. However, in the presence of measurement errors in the river flow time series, the use of the KF technique assumes relevance.

For this purpose, the data of 10 rivers recorded at 10 flow gauge stations, in northern Algeria, have been considered for the application of the methodologies used in this paper. Here, we are focusing particularly upon streamflows, because they are directly linked to any social, economic, or environmental developments, but the idea still remains applicable for any other hydrological variable.

2. Theoretical backround

Two different types of stochastic models have been investigated in the present study. The first one deals with Box–Jenkins (BJ) procedure, a classic method that is based on the serial dependence structure of data, working under the restrictive assumptions of stationarity and normality. The second one is concerned with the KF, which is based on the least squares concept and well known by its optimality provided that the assumptions of linearity and white Gaussian noise are valid.

2.1. Box–Jenkins models

Any time series, Y_t, can be considered as the output of a linear system, where input ε_t is a white Gaussian noise, such as:

$$Y_t = \mu + \psi(B)\varepsilon_t \tag{1}$$

Here, μ is the mean of Y_t, B is the back shift operator such as $B^k\varepsilon_t = \varepsilon_{t-k}$, for k = 1, 2 … and $\psi(B)$ is the transfer function, which links the input, ε_t, to the linear system output, Y_t, such as $\psi(B) = 1 + \psi_1 B + \psi_2 B^2 + \psi_3 B^3 \cdots$.

A particularly interesting class of these models is the autoregressive (AR) one. In such a model, every value Y_t is the weighted and finite sum of previous values plus a random term, ε_t. The model is then designated by AR (p), p being the corresponding order. Hence, for a zero mean, it is expressed as follows:

$$\phi(B)Y_t = \varepsilon_t \tag{2}$$

where $\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \ldots - \phi_p B^p$, is the AR ($p$) operator, which is a p order polynomial in B, which converges for $|\phi_i| < 1$ in order to insure the stationary condition

Another interesting model is the moving average (MA) approach, in which each value is the sum of $q + 1$ previous values of a white noise as:

$$Y_t = \theta(B)\varepsilon_t \tag{3}$$

Herein, $\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_p B^p$, is the MA ($q$) operator, which is a q order polynomial in B, and itconverges for $|\theta_i| < 1$ in order to insure for invertibility condition insurance.

The combination of AR (p) et MA (q) models is a another type of model, which is a linear mixed process called auto regressive and moving average of order p and q, ARMA (p, q) and it is expressed as follows.

$$\phi(B)Y_t = \theta(B)\varepsilon_t \tag{4}$$

In this case, when the input ε_t is a white Gaussian noise, Y_t, can be considered as the output of a linear filter whose transfer function is the ration of two polynomials, namely, $\theta(B)$ and $\phi(B)$:

$$Y_t = \frac{\theta(B)}{\phi(B)_t}\,\varepsilon_t \tag{5}$$

This type of modeling assumes data to be stationary, but this is not the case in most of hydrological time series. For instance, a time increase in the variance, average level or variance instability is frequently observed denoting a linear trend or seasonal variations in the considered time series. In this case, it is always possible to make them stationary via some mathematical transformations. Hence, ARMA model becomes ARIMA, and accordingly, seasonal ARIMA is denoted as SARIMA model.

More details on the method can be found in the classic references [7–10] or in the more recent ones [11–13] among others, whereas practical applications can be found in [14–16]. Regarding the BJ models parameters estimation, the maximum likelihood method has been adopted.

2.2. *Kalman filter*

The Kalman filter (KF) is considered to be one of the most well-known and often-used significant mathematical tools that can be used for stochastic estimation from noisy measurements [17]. It is as an optimal recursive data-processing algorithm, which is constituted essentially by a set of five mathematical equations that implement a predictor–corrector-type estimator that is optimal in the sense that it minimizes the estimated error covariance, when some presumed conditions are met. Those equations are recursive and present the main advantage to provide the prediction error accurately:

$$\hat{X}_{\mathrm{k/k}} = \hat{X}_{\mathrm{k/k-1}} + K_{\mathrm{k}}\left(Z_{\mathrm{k}} - H_{\mathrm{k}}\,\hat{X}_{\mathrm{k/k-1}}\right) \tag{6}$$

$$K_{\mathrm{k}} = P_{\mathrm{k/k-1}}\,H_{\mathrm{k}}^{\mathrm{T}}(H_{\mathrm{k}}\,P_{\mathrm{k/k-1}}\,H_{\mathrm{k}}^{\mathrm{T}} + R_{\mathrm{k}})^{-1} \tag{7}$$

$$P_{\mathrm{k/k}} = (\mathrm{I} - K_{\mathrm{k}}\,H_{\mathrm{k}})\,P_{\mathrm{k/k-1}} \tag{8}$$

$$\hat{X}_{\mathrm{k+1/k}} = \phi_{\mathrm{k+1/k}}\,\hat{X}_{\mathrm{k/k}} \tag{9}$$

$$P_{\mathrm{k+1/k}} = \phi_{\mathrm{k+1/k}}\,P_{\mathrm{k/k}}\,\phi_{\mathrm{k+1/k}}^{\mathrm{T}} + Q_{\mathrm{k}} \tag{10}$$

In addition, KF can be initiated with minimum available objective information, and it is adaptable as soon as a new observation arrives. It has been the subject of extensive research and application, in many areas [17–22] among others. This is not only due to the great developments in digital computing that made practical use of the filter, but also to the simplicity and the robustness of the filter itself.

3. Obtained results and discussion

The data considered in the present study are the annual and monthly streamflow time series recorded by the National Agency for Hydraulic Resources (ANRH) in Algeria. They are observed during different periods of time with a common period of 25 years (1968–1992) that is utilized for testing. Those data belong to mainly two subareas, namely the eastern part with four hydrometric stations that is characterized by the abundance of precipitation and the western part wherefive hydrometric stations are characterized by the scarcityof precipitation amounts. Fig. 1 provides the spatial repartition of the considered stations.

3.1. *Annual scale modeling*

3.1.1. *Box–Jenkins (BJ) method*

In order to apply the BJ approach, it is necessary to divide the data into training and testing parts. Herein, last 25 years were left for validation, whereas all other values were utilized for training.

As mentioned before, BJ method works principally on the serial dependence structure of time series under the assumption that they are stationary. Therefore, the results of the annual streamflow modeling led to five ARIMA models, for the stations situated in the western and central parts of northern Algeria (see Fig. 1), while for the Eastern part, Ainberda, Bouchegouf, Cheffia, Mirebeck, time series did not present any autocorrelation structure. For each one of the time series, five other models were adjusted and estimated, and the best fit is retained based on some statistical criteria.

Fig. 1. Location of the concerned hydrometric stations in northern Algeria.
Source: K. Boukharouba, A. Kettab, Kalman filter technique for multi-site modeling and stream flow prediction in Algeria, J. Food Agric. Environ. 7(2) (2009) 671–677. WFL Publisher Helsinki, Finland.

The goodness-of-fit statistics are the mean square error (MSE) and the determination coefficient (R^2) of the streamflow values, during training as well as validation periods, as presented in Table 1. The MSE statistic is a measure of the residual variance and it is indicative of the model's ability to perform predictions. The R^2 is a measure of the variance that is explained by the concerned model. Hence, the best-fit model is the one with the lowest MSE and the highest R^2 values for both training and testing. For the retained ARIMA models, the MSE and R^2 statistics, for both estimation and validation periods, confirm the ability of those models to predict annual streamflows.

From another point of view, the obtained models confirm the predominance of the random character of the concerned data in the eastern part, relatively to the western side. This random character is prevalent even for the dependent data in the western part because, five models together explain an average of 63.07% only from the total variance. The random character is then around 36.93% for the annual streamflows at the study area. The models parameters estimation is provided by Table 2.

Fig. 2 illustrates only one example of the application of BJ method to the modeling of annual streamflow time series. It provides the observed and estimated annual values at Ksob from 1968 to 1992. The obtained predictions follow roughly the observed values, and the corresponding errors are relatively important. This is obtained with the best-fit model (among 5 others), which explains about 62.5% of the total variance.

Table 1
BJ modeling of annual stream flows

No.	Station	Model	MSE (training)	MSE (testing)	R^2 (training)	R^2 (testing)
1	Ainberda	–	–	–	–	–
2	Bénibahdel	ARIMA (0, 1, 2)	901.67	809.39	30.89	37.90
3	Bouchegouf	–	–	–	–	–
4	Bouhnifia	ARIMA (1, 0, 3)	1,416.25	1,011.66	65.02	75.01
5	Cheffia	–	–	–	–	–
6	Ksob	ARIMA (2, 0, 0)	207.72	191.00	59.23	62.5
7	Mefrouche	ARIMA (2, 0, 3)	28.74	23.41	65.97	72.28
8	Mirebeck	–	–	–	–	–
9	Pierre du chat	–	–	–	–	–
10	Remchi	ARIMA (1, 0, 3)	5.81	4.98	62.32	67.70
	Average					63.07

Table 2
Annual streamflows BJ modeling parameters

Annual model	Parameters							
	AR (1)	AR (2)	AR (3)	MA (1)	MA (2)	MA (3)	Constant	Residuals variance
ARIMA (0, 1, 2)	–	–	–	0.4666	0.4724	–	–	–
ARIMA (1, 0, 3)	−0.7834	–	–	−1.1216	−0.8191	−0.6753	268.41	3,031.81
ARIMA (2, 0, 0)	−0.0224	0.6569	–	–	–	–	13.22	487.31
ARIMA (2, 0, 3)	0.5167	−0.5861	–	0.5101	−0.3171	−0.5441	17.22	71.67
ARIMA (1, 0, 3)	0.4918	–	–	0.2457	0.1614	−0.4760	5.38	10.91

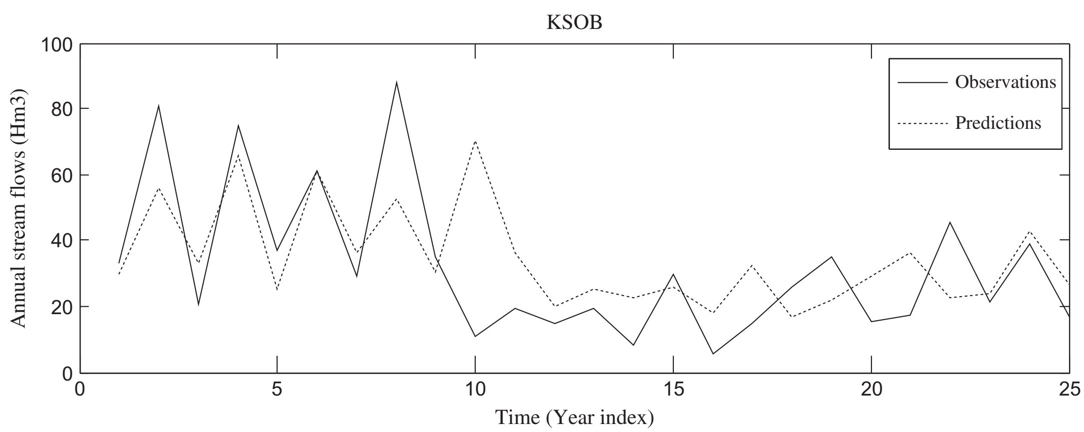

Fig. 2. Box–Jenkins annual predictions at KSOB station (1968–1992).

3.1.2. Kalman filter (KF) method

For the same 10 hydrometric stations, KF has been applied to generate multisite annual predictions with a common observation period of 25 years (1968–1992). An example of this application is illustrated in Fig. 3 for Ksob during the above mentioned 25 years period. It is to be noticed from this figure that the observed and predicted values follow each other closely, and this is indicative of the KF efficiency for the modeling of annual streamflow values. Prediction error is unavoidably greater at the beginning, where more confidence is paid to records than to the model with a

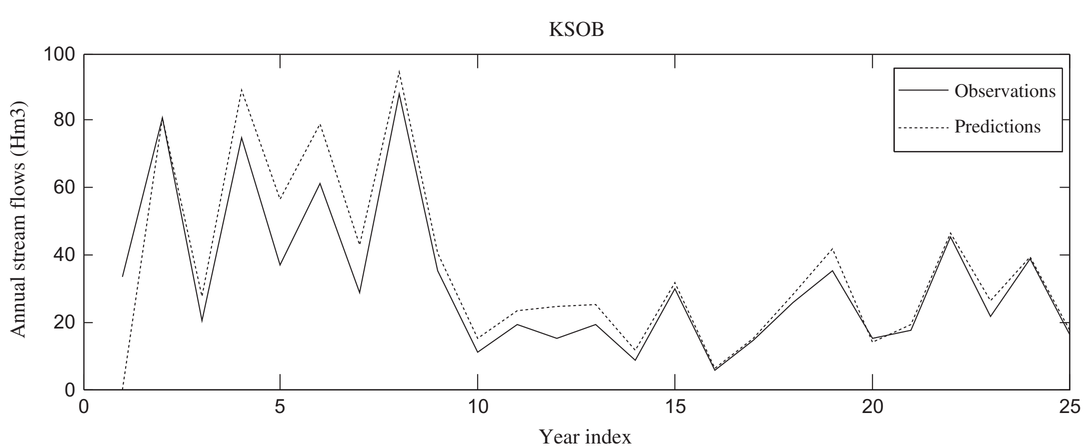

Fig. 3. Kalman filter annual predictions and prediction errors at Ksob hydrometric station for 25 years period (1968–1992).

Table 3
Comparison of prediction error between KF and BJ models (1968–1992)

Statistic	Bénibahdel		Bouhnifia		Ksob		Mefrouch		Remchi	
	FK	BJ	FK	BJ	FK	BJ	FK	BJ	FK	BJ
Mean	−1.55	−21.52	−3.65	−44.87	−0.55	−5.00	0.13	−5.55	0.65	−30.27
Std	5.10	19.08	10.65	47.57	4.98	18.91	1.92	7.80	6.01	41.96
Min	−11.46	−53.81	−21.19	−101.08	−10.24	−59.27	−2.78	−18.87	−8.43	−88.28
Max	6.35	10.03	13.56	38.76	13.85	35.01	5.34	8.97	14.63	66.65

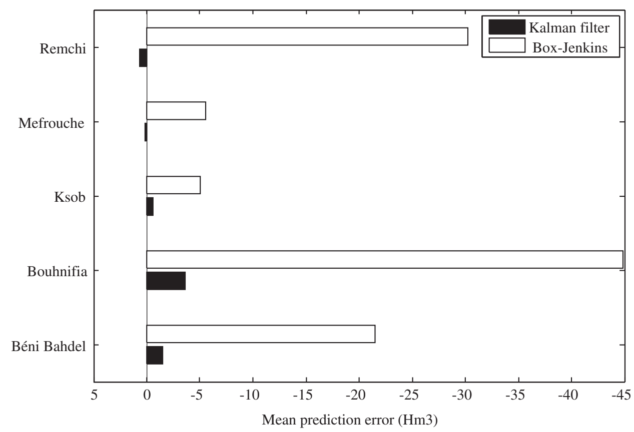

Fig. 4. Mean prediction error for the KF and BJ models.

big Kalman gain, but after some iterations the model becomes more confident than observation with a lesser Kalman gain and predictions are definitively better.

The major objective of this paper is to answer the question, which is better for the prediction of streamflow values in the area of study, KF or BJ model? For this purpose, a comparison between the two models is accomplished via some statistics of the prediction error, so as the mean, standard deviation, and the extreme values, as provided in Table 3.

According to those results, it is obvious that KF prediction errors statistic values are lesser (in absolute value) than the BJ ones. Fig. 4 is a graphical representation of such comparison in terms of mean only, whereas the same thing can be done for the remaining statistics. This means that the difference between the observed streamflow values and their predictions are smaller by KF than by BJ model. Hence, it can be argued that regarding the annual streamflow prediction, KF performs better.

3.2. Monthly scale modeling

3.2.1. Box–Jenkins (BJ) method

BJ modeling procedure of monthly streamflows observed at the concerned hydrometric stations led to the determination of ten stochastic seasonal models. Every one of which has been identified and estimated together with 5 others, and hence, the most suitable one has been selected based on the residual variance. The lesser is the residual variance, the better is the model. It is to be noticed that all monthly time series needed some transformations to be stationary, but the average explained variance of the whole models is around 73.37% (Table 4). This value shows that the seasonal effect has increased the correlated structure

Table 4
BJ models obtained for monthly scale

No.	Station	Model	MSE (training)	MSE (testing)	R^2 (%) (training)	R^2 (%) (testing)
1	Ainberda	SARIMA $(1, 0, 0) \times (0, 1, 1)_1$	04.74	02.79	52.6	72.1
2	Bénibahdel	SARIMA $(1, 1, 1) \times (2, 1, 1)_1$	47.34	15.85	54.36	84.71
3	Bouchegouf	SARIMA $(1, 0, 0) \times (0, 1, 1)_1$	177.65	103.25	47.74	53.4
4	Bouhnifia	SARIMA $(1, 1, 1) \times (0, 1, 1)_1$	155.90	64.03	64.84	85.56
5	Cheffia	SARIMA $(1, 1, 1) \times (0, 1, 1)_1$	301.22	246.25	64.55	71.02
6	Ksob	SARIMA $(0, 0, 3) \times (0, 1, 1)_1$	13.01	12.98	55.65	55.76
7	Mefrouch	SARIMA $(1, 0, 0) \times (0, 1, 1)_1$	03.59	1.18	29.05	76.67
8	Mirebeck	SARIMA $(2, 0, 0) \times (0, 1, 1)_1$	2,428.46	1,240.27	49.43	74.17
9	Pierre du chat	SARIMA $(1, 0, 0) \times (1, 1, 1)_1$	215.17	200.86	69.65	71.66
10	Remchi	SARIMA $(0, 0, 1) \times (0, 1, 1)_1$	99.07	39.60	71.85	88.74
	Average					73.37

Table 5
Monthly streamflows BJ modeling parameters

Monthly model	Parameters							
	AR (1) SAR (1)	AR (2) SAR (2)	AR (3) SAR (3)	MA (1) SMA (1)	MA (2) SMA (2)	MA (3) SMA (3)	Constante	Residuals variance
SARIMA (1, 0, 0) (0, 1, 1)$_{12}$	0.2810	–	–	–	–	–	–	4.87
	–	–	–	**0.9563**				
SARIMA (1, 1, 1) (2, 1, 1)$_{12}$	0.2399	–	–	0.9702	–	–	–	47.74
	0.2057	**0.0731**	–	**0.9658**				
SARIMA (1, 0, 0) (0, 1, 1)$_{12}$	0.2844	–	–	–	–	–	–	192.07
	–	–	–	**0.9511**				
SARIMA (1, 1, 1) (0, 1, 1)$_{12}$	0.1350	–	–	0.9599	–	–	–	154.76
	–	–	–	**0.9688**				
SARIMA (1, 1, 1) (0, 1, 1)$_{12}$	0.1092	–	–	0.9211	–	–	–	306.04
	–	–	–	**0.8960**				
SARIMA (0, 0, 3) (0, 1, 1)$_{12}$	–	–	–	−0.2688	−0.2102	−0.3041	−0.21	13.55
	–	–	–	**0.9623**				
SARIMA (1, 0, 0) (0, 1, 1)$_{12}$	0.1786	–	–	–	–	–		3.78
	–	–	–	**0.9617**				
SARIMA (2, 0, 0) (0, 1, 1)$_{12}$	0.2695	0.1818	–	–	–	–	−0.67	2410.76
	–	–	–	**0.9677**				
SARIMA (1, 0, 0) (1, 1, 1)$_{12}$	0.2971	–	–	–	–	–		617.70
	0.2218	–	–	0.9574				
SARIMA (0, 0, 1) (0, 1, 1)$_{12}$	–	–	–	−0.1144	–	–	−0.17	315.80
	–	–	–	**0.9668**				

Note: Bold values indicate seasonal parameters.

of the data. Consequently, their random character has been relatively decreased to reach the value of 26.63% instead of 36.93% for the annual scale. The models parameters have been estimated by the maximum likelihood method and are given in Table 5.

An example of the predictions is illustrated in Fig. 5 for Pierre du Chat from October 1968 to August 1992. It is obvious from this figure that predictions follow observations in their whole pattern, but the peak-values are not reproduced by the model. This behavior has been noticed for the remaining models too and may denote an underlying tendency of the BJ models to underestimation.

3.2.2. Kalman filter (KF) method

KF predictions are obtained via a multisite operator, where predictions in the considered hydrometric stations are obtained simultaneously (Fig. 6). It shows both observations and predictions by the KF for the monthly streamflows at Pierre du Chat station during the period of September 1968 to August 1992. It is

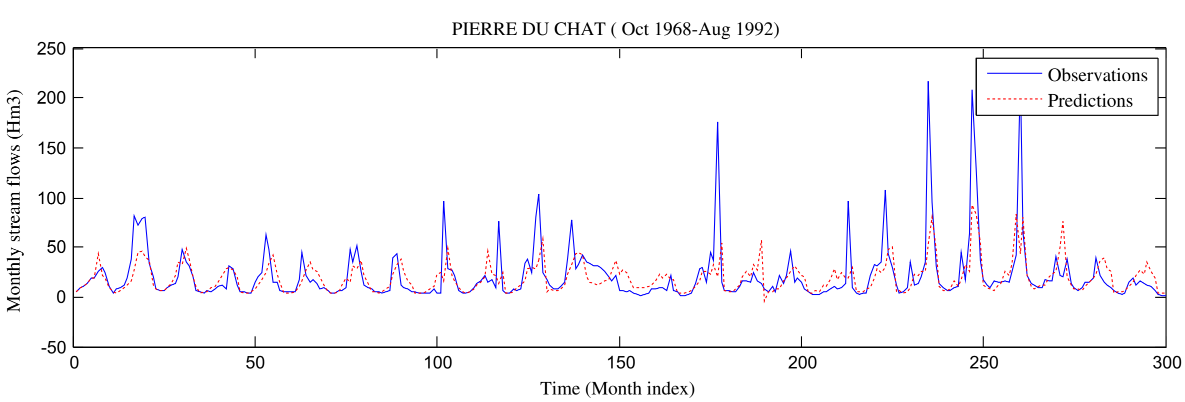

Fig. 5. Box–Jenkins monthly predictions at PIERRE DU CHAT (October 1968–August 1992).

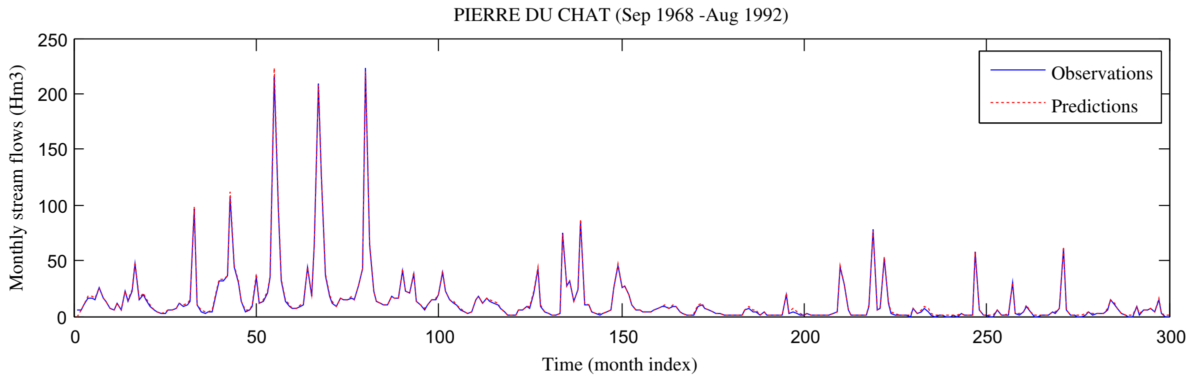

Fig. 6. Kalman filter monthly predictions and corresponding prediction error at PIERRE DU CHAT station (October 1968–August 1992).

Table 6
Comparison of monthly prediction errors between KF and BJ models (1968–1992)

	Ainberda		Bénibahdel		Bouchegouf		Bouhnifia		Cheffia	
Statistic	FK	BJ	FK	BJ	FK	BJ	FK	BJ	FK	BJ
Mean	−1.22	0.04	−0.53	0.30	−0.62	−0.61	−0.78	1.47	−0.98	0.04
Std	1.69	2.13	1.01	5.24	0.81	12.98	1.16	9.99	1.77	16.96
Min	−17.01	−3.95	−8.79	−12.57	−8.36	−24.75	−12.48	−18.27	−18.58	−39.28
Max	1.69	16.45	6	27.75	0.32	86.86	0	94.34	1.56	89.95
	Ksob		Mefrouch		Mirebeck		Pierre du chat		Remchi	
Mean	−1.69	0.03	−0.23	0.05	−1.90	1.58	−1.43	2.15	−0.51	1.45
Std	2.84	3.64	0.89	1.84	2.91	45.69	1.89	24.36	0.79	17.71
Min	−28.2	−6.17	−5.36	−3.58	−26.8	−93.93	−19.68	−55.91	−6.27	−19.42
Max	1.23	21.20	5.85	16.97	0	417.00	1.72	179.88	5.34	161.98

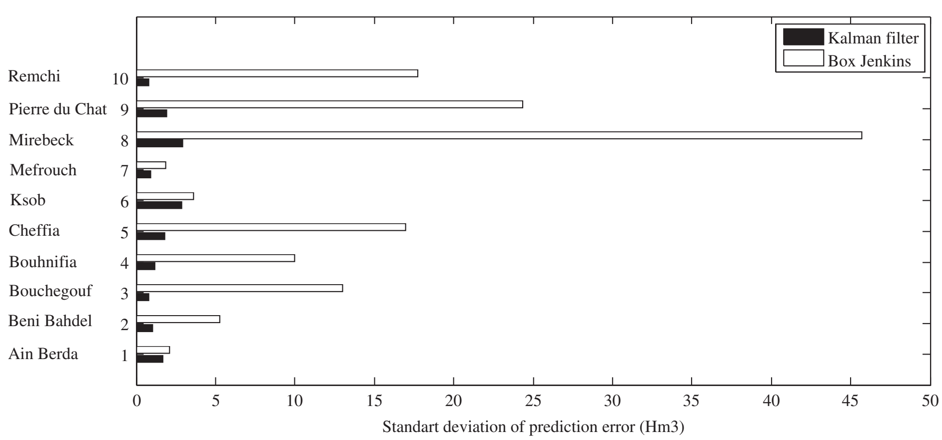

Fig. 7. Monthly prediction error standard deviation for both of KF and BJ models.

obvious that predictions follow the corresponding observations very closely. The predictions are unavoidably bad at the beginning of calculations because more attention is accorded to the observations, but just after some iteration, more confidence is accorded to the model, hence the errors become lesser and predictions are better.

For each one of the concerned stations, Table 6 gives the comparison between KF and BJ monthly prediction error via the mean, standard deviation, minimum and the maximum values. The calculated statistics of the prediction error show that values of all the considered statistics are significantly different from KF to BJ models. An average of the indicated statistics absolute values has been calculated over the 10 hydrometric stations, and it is found that the standard deviation, the KF value is 9-fold smaller compared to the BJ model, the minimum value is twice fold smaller for KF and the maximum is also 47-fold smaller for KF. Once again, this is indicative of the superiority of KF over BJ for the prediction of monthly streamflow values in the study area. Fig. 7 shows as the standard deviation and it denotes an eventual tendency of KF for the underestimation.

4. Summary and conclusion

In this study, the potentials of Box–Jenkins (BJ) and Kalman-filtering (KF) techniques are investigated for modeling streamflow hydrological time series prediction in northern Algeria. The principal objective is to compare their results and to find which one performs better predictions in the area. BJ technique has been applied for annual and monthly streamflow time series. For the annual data, obtained results led to the determination of five ARIMA models with an overall mean explained variance of 63%, in addition to the confirmation of the random character preponderance with 37% amount, whereas for the monthly streamflows 10 seasonal SARIMA models have been determined with an overall mean explained variance at around 75%. The random character is consequently decreased to reach 25%.

On the other hand, KF methodology has been applied for annual and monthly streamflow multisite prediction and the result is an on-line operation, where temporal and spatial optimal predictions are obtained both for monthly and annual scales. The prediction errors are then compared to those of Box–Jenkins and it is found that KF performs better predictions for annual stream flows as well as for monthly ones. The prediction error standard deviation value for KF is 9 folds smaller than that of BJ models, the minimum and maximum values are respectively 2 and 47 folds smaller. This denotes the efficiency and superiority of KF for prediction of streamflow values in the study area. An eventual tendency of KF to the underestimation has also been noticed from the prediction error standard deviation illustration.

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