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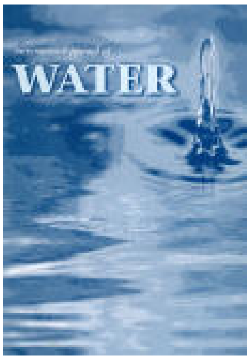

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Influence of climate type on the predictive capabilities of stochastic models applied to monthly dam inflows

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Abstract: This contribution assesses the predictive capacity of monthly inflow of two stochastic models called autoregressive integrated moving average (ARIMA) and TBATS and highlights the influence of climate type on their performances. These are the inflows to three dams in three distinct climates: semi-arid, subhumid and humid. The actual inflows are deduced from the water balance equation for 132-month period. The first ten corresponding years of each series are used for training of the two models and the last one is then used for test. Model performances are evaluated using three commonly used metrics: the square root of the mean square error (RMSE), the mean of the absolute errors (MAE), and the mean absolute error in percentage (MAPE). The results show that the TBATS model performs better than the ARIMA model and its predictive capabilities decrease depending on whether the climate is semi-arid, sub-humid and humid (MAPE = 50.47%, 34.79% and 29.99%, respectively).

Keywords: ARIMA; autoregressive integrated moving average; TBATS; trigonometric, box-cox transform, ARMA errors, trend and seasonal components; climate type; forecast; monthly dam inflows; stochastic models; time series; predictive capabilities.

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1 Introduction

The importance of water as a vital resource and a major factor in the country's development is globally recognised. Its quantification and management must be rigorous (Bouanani, 2004). In this context, it is easy to understand the need to develop models as management and decision support tools (Perrin et al., 2003). Hydrological predictions using various models are intended to allow for more informed planning, both for flood or dry conditions and for ordinary hydrological conditions.

In the literature, there are several approaches to model time series, the most frequently used forecasting methods are those based on exponential smoothing models (Winters, 1976), ARIMA models (integrated moving average autoregressive) (Box et al., 2015) and TBATS models (trigonometric exponential smoothing, Box-Cox transformation, ARMA residues, trend and seasonal parts) (De Livera et al., 2011). Among the many algorithms implemented for forecasting, exponential smoothing methods represent a significant role in identifying the model for annual, quarterly and monthly data. Still, most of these approaches are generally unable to deal with time series of very large sizes, recorded with high frequency, such as daily or hourly scale data (Gos et al., 2020).

Stochastic models are mainly used to analyse fluctuations in stream runoff and by analogy are suitable for predicting liquid inflows within reservoir dams at different time scales (Dahkal, 2015; Abd Saleh, 2013; Gupta and Kumar, 2020). Stochastic models widely used for forecasting time series called ARIMA are also known as Box-Jenkins linear stochastic approaches (Box et al., 2015; Moeeni et al., 2017). These require long time series data for analysis, at least 50–100 observations are needed for a vigorous result. TBATS models are also used in several research fields, thus providing an alternative to ARIMA types through the possibility of processing chronological variables with complex and dynamic seasonality (Gould et al., 2008; De Livera et al., 2011; Taylor and Snyder, 2012; Gos et al., 2020; Herbert et al., 2021). These models govern the specific nonlinear phenomena that are often observed in real-time series and adapt to any autocorrelation in the residuals. The primary benefit of TBATS models is that the trigonometric component may be considered for data with a high seasonal frequency (De Livera et al., 2011).

This paper aims to assess the forecasting capacities of two time series models named ARIMA and TBATS, through the monthly dam inflows, and highlights the influence of climate type on their accuracy. For long-term forecasting (annual flows, trend for the next few years), climate trends must be taken into account (Fortin et al., 1997).

The actual monthly inflows to be modelled are deduced from the water balance equation based on the mass conservation concept, which is adopted by the national agency for dams and transfers (NADT) to manage all dams in Algeria in terms of water resources. The three dams: Hammam Boughrara, Beni Haroun and Taksebt, objects of the present study, are respectively selected based on a climatic variability from semi-arid, subhumid to humid according to the classification of Hildebert (1950). These three reservoirs mobilise and regulate water for multiple purposes.

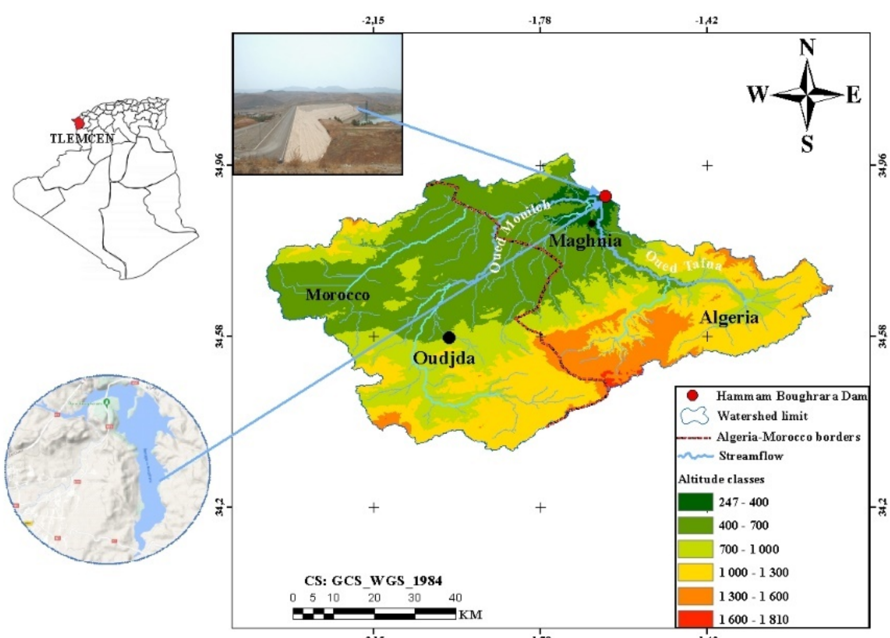
2 Materials and methods

2.1 Study area and brief description of dams

2.1.1 Hammam Boughrara dam (semi-arid climate)

The Hammam Boughrara earth dam is situated on the Tafna wadi, 13 km east of the city of Maghnia in western Algeria and at the confluence of the Mouillah river with the Tafna wadi. It was officially launched in 1999, with an initial capacity of 177 Mm^3, with the main objective of supplying drinking water to the cities of Oran and Maghnia. The dam receives surface water from the Oued Mouillah watershed (2000 km^2) shared between Algerian and Moroccan territory (Figure 1). This basin is composed in its majority by the plains of Angad (Oujda, Morocco) and Zrigua (Maghnia, Algeria) (Dahmani et al., 2018).

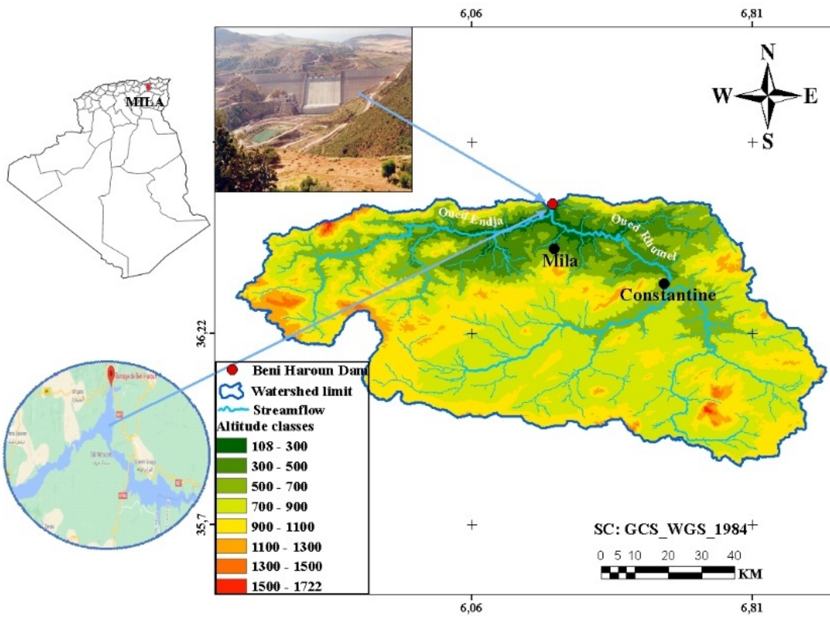
Figure 1 Geographical location of the Hammam Boughrara dam (semi-arid case) (see online version for colours)



2.1.2 Beni Haroun dam (subhumid climate)

The Beni Haroun compacted concrete dam is a major strategic hydraulic structure in Algeria (Figure 2). The total volume of its reservoir is 997 Mm^3. The site of the dam is situated in the wilaya of Mila, in the east of Algeria on the Oued El Kebir. The reservoir generated by the dam is located to the south of the dam. It is located about 40 km north/northwest of the city of Constantine and 350 km east of Algiers. The total basin of Oued Kebir at the site of the dam has an area of 7725 km^2. Taking into account that part of the Rhumel basin is mobilised by the Hammam Grouz dam, the area related to the Beni Haroun dam is about 6595 km^2 (LEM, 2013). The dam provides drinking water to the cities of Mila, Constantine, Jijel, Oum-El-Bouaghi, Khenchela and Batna as well as the irrigation of orchards in Mila.

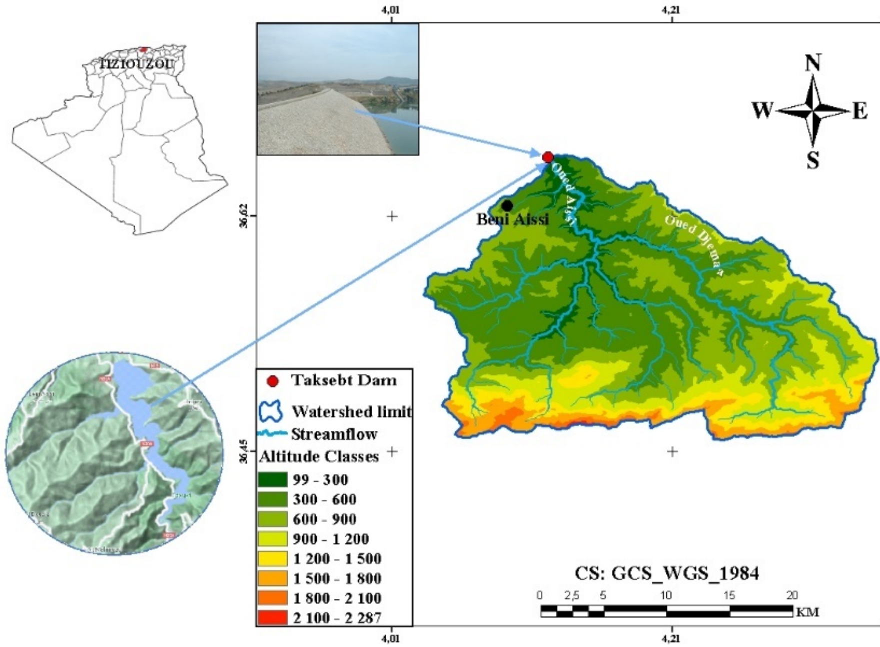
Figure 2 Geographical location of the Beni Haroun dam (subhumid case) (see online version for colours)



2.1.3 Taksebt dam (humid climate)

The Taksebt earth dam is situated on the wadi Aissi, 10 km east of the city of Tizi-Ouzou in central of Algeria (Figure 3). It was officially launched in 2001 to provide drinking water to the cities of Tizi-Ouzou and Algiers. The dam receives an average annual inflow of 196 Mm^3 from a catchment area of 448 km^2. The Taksebt dam has greatly contributed to the improvement of drinking water supply at the rate of 73 Mm^3 annually for the wilaya of Tizi-Ouzou, as well as the other irrigated basins, Algiers, Blida and Boumerdes (Smadi and Abrika, 2018).

Figure 3 Geographical location of the Taksebt dam (humid case) (see online version for colours)



2.2 Data

The used database was collected from the National Agency for Dams and Transfers (NADT). It consists of time series concerning the elements constituting the water balance within the three dams; Hammam Boughrara, Beni Haroun and Taksebt, expressed in millions of cubic meters (Mm^3), according to the following conservation equation of mass or volume:

$$Inflow = \left(V_{ini} - V_{fin}\right) + \left(EVA + DWS + IRR + RVS + VID + LEA\right) \quad (1)$$

With:

Inflow: volume of the overall inflows of the dam; V_{ini}: stored volume at time (t); V_{fin}: stored volume at time (t+1); *EVA*: evaporated volume; *DWS*: volume allocated to drinking water supply; *IRR*: volume allocated to irrigation; *RVS*: released volume by spillway; *VID*: emptying volume; *LEA*: leakage volume.

The monthly dam inflows at the concerned reservoirs are deduced from equation (1) adopted by NADT to manage all the dams in Algeria in terms of water resources.

The period at the monthly scale, thus serving as a basis for this contribution, extends from 01/01/2002 to 31/12/2012, 01/01/2009 to 31/12/2019 and 01/01/2003 to 31/12/2013, i.e., 11 years of observation for the three dams Hammam Boughrara, Beni Haroun and Taksebt, respectively. The sizes of the three series are identical (132 months), which eliminates the direct influence of the length of the sample in favour of an expected and probable climate influence. The numerical values of the monthly inputs within the three dams vary from 0.446 Mm^3 to 44.569 Mm^3, 7.614 Mm^3 to 686.034 Mm^3

and 0.297 Mm^3 to 102.028 Mm^3 for Hammam Boughrara, Beni Haroun and Taksebt, respectively. For the models considered in this work, the training phase is spread over the first ten years and the test phase concerns the last year for each dam studied separately.

2.3 ARIMA models

One of the well-known ways of time series modelling is the ARIMA modelling introduced by Box and Jenkins to forecast time series (Box et al., 2015).

The ARIMA or Box-Jenkins models are relatively easy to implement (Hyndman and Khandakar, 2008). A seasonal ARIMA model is denoted ARIMA (autoregressive integrated moving average, (p, d, q) $(P, D, Q)s$, the data depend on the previous values (not seasonal part) and also on the values for the same period of previous years (seasonal part) where s is the seasonal period which is equal to 12 for the monthly case.

An ARIMA (p, d, q) (non-seasonal part) model can take into account time dependence in several ways. First, the time series is differentiated to make it stationary. If $d = 0$, the observations are modelled directly, and if $d = 1$, the differences between consecutive observations are modelled. Second, the time dependence of the stationary process y_t is modelled by including p autoregressive models. Third, q are terms of the moving average models. The process supports the observation of previous errors. Finally, by combining these three models, we obtain the ARIMA model. Thus, the general form of ARIMA models is given by:

$$y_t = c + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} \tag{2}$$

where y_t and y_{t-i} are stationary stochastic processes at time t and t-i, c is the constant which determines the level of the time series, ε_t is the error or white noise term, ϕ_i mean the autoregressive coefficients and θ_j are the moving average coefficients.

For a seasonal part, these steps can be repeated according to the cycle period, regardless of the time interval. The process is the same for the seasonal part as for $D \neq 0$.

2.4 TBATS models

The main disadvantage of the ARIMA approach is that seasonality is forced to be periodic, while a TBATS model allows multiple, complex and dynamic seasonality in time series (Gould et al., 2008). TBATS is an alternative developed by (De Livera et al., 2011). This model uses a mixture of the terms of Fourier and an exponential smoothing fit with a fully automated Box-Cox transformation (Hyndman, 2017). The TBATS model can be stated as follows:

For a time-series y_t of N observed data, we define a Box-Cox transformation with the parameter ω as follows:

$$y_t^{\omega} = \begin{cases} \dfrac{y_t^{\omega} - 1}{\omega}, & \omega \neq 0 \\ \log\left(y_t\right), & \omega = 0 \end{cases} \tag{3}$$

Then we have:

$$y_t^{\omega} = l_{t-1} + \phi b_{t-1} + \sum_{i=1}^{V} S_{t-m_i}^{i} + d_i \tag{4}$$

where $l_t = l_{t-1} + \phi b_{t-1} + \alpha d_t$ is the local level in the period t, $b_t = (1-\phi)b + \phi b_{t-1} + \beta d_t$ is the short term trend of period t with b is the long term trend, $d_t = \sum_{i=1}^{p} \phi_i d_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t$ refers to a model ARMA(p, q) with the parameters ϕ_i (for $i = 1, \ldots, p$), θ_i (for $i = 1, \ldots, q$) and ε_t is a white noise. The ith seasonal element at time t is defined as: $S_t^i = S_{t-m_i}^i + \gamma_i d_t$. The smoothing coefficients are given by α, β, γ_i, for $i = 1, \ldots, u$, to determine the extent of the effect of irregular components on the states b_t^i, $l_t^i \; et \, S_t^i$, respectively. The main difference between TBATS and other seasonal formulations is the use of ARMA and the transformation of Box-Cox, which allows additional information to be captured in the data. Gos et al., (2020) say that De Livera et al. (2011) are amended the approach of West and Harrison (2006) and introduce the TBATS model, written as TBATS (ω, ϕ, p, q, (m_1, k_1), (m_2, k_2), …, (m_u, k_u)), (Gos et al., 2020). The term k_i is the number of harmonics for the seasonal component S_t^i. The TBATS model achieves typical non-linear features that are often observed in real-time series and adapts to any autocorrelation in the tailings. The TBATS model is also built on the Fourier transformation. In this model, the ith seasonal element S_t^i is defined by following a system of equations which is written:

$$\begin{pmatrix} S_t^i = \sum_{j=1}^{k_i} S_{j,t}^i \ , \\ S_{j,t}^i = S_{j,t-1}^i cos\eta_j^i + S_{j,t-1}^{'i} sin\eta_j^i + \mu_1^i d_t \, , \\ S_{j,t}^{'i} = -S_{j,t-1}^i sin\eta_j^i + S_{j,t-1}^{'i} cos\eta_j^i + \mu_2^i d_t \end{pmatrix} \tag{5}$$

where μ_1^i and μ_2^i are the smoothing coefficients and $\eta_j^i = \frac{2\pi j}{m_i}$ describes the stochastic level of the ith seasonal element as being $S_{j,t}^i$ and $S_{j,t}^{'i}$ for stochastic growth of the ith seasonal element and describes seasonal changes over time. The number of k_i harmonics required for the ith seasonal component is defined as follows: $k_i = \frac{m}{2} or \frac{m-1}{2}$, if m is even or odd, respectively.

2.5 *ARIMA/TBATS candidate model choice criteria*

The best ARIMA/TBATS forecasting models are those that meet the most recognised quality criterion known as the Akaike Information Criterion (AIC), (Akaike, 1974). This last criterion leads to the choice of the model with the smallest mean square error by applying a penalty which depends on the quantity of unknown parameters that must be estimated. Therefore, this criterion favours parsimonious models and is calculated by the following relationship:

$$AIC = 2k - 2\log(L) \tag{6}$$

where k is the number of coefficients estimated in the model and L denotes the maximum value of the likelihood function for the model.

2.6 Performance criteria

Various statistical measures have been developed and used in the literature. To assess the fit and predictive accuracy of the models in this contribution, the datasets were mathematically evaluated by calculating and restricting to the following three performance criteria: The square root of the mean squared error (*RMSE*), the mean absolute errors (*MAE*) and mean absolute percentage error (*MAPE*) expressed by the following equations:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(M_i - P_i)^2} \tag{7}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|M_i - P_i\right| \tag{8}$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{(M_i - P_i)}{M_i}\right| \times 100 \tag{9}$$

where N is the amount of data points (size of the time series), M_i are the measured values and P_i are the corresponding predicted values.

One of the most frequently used metrics to evaluate the accuracy of the model's predictions is *MAPE*, which is the *MAE* in percent. This performance indicator is easy to interpret. For example, a x% value of *MAPE* means that the average variance among the predicted and the measured values is x%. The *MAPE* metric will be adopted for the final selection of the best model in this study.

3 Results and discussions

3.1 Results related to the semi-arid case

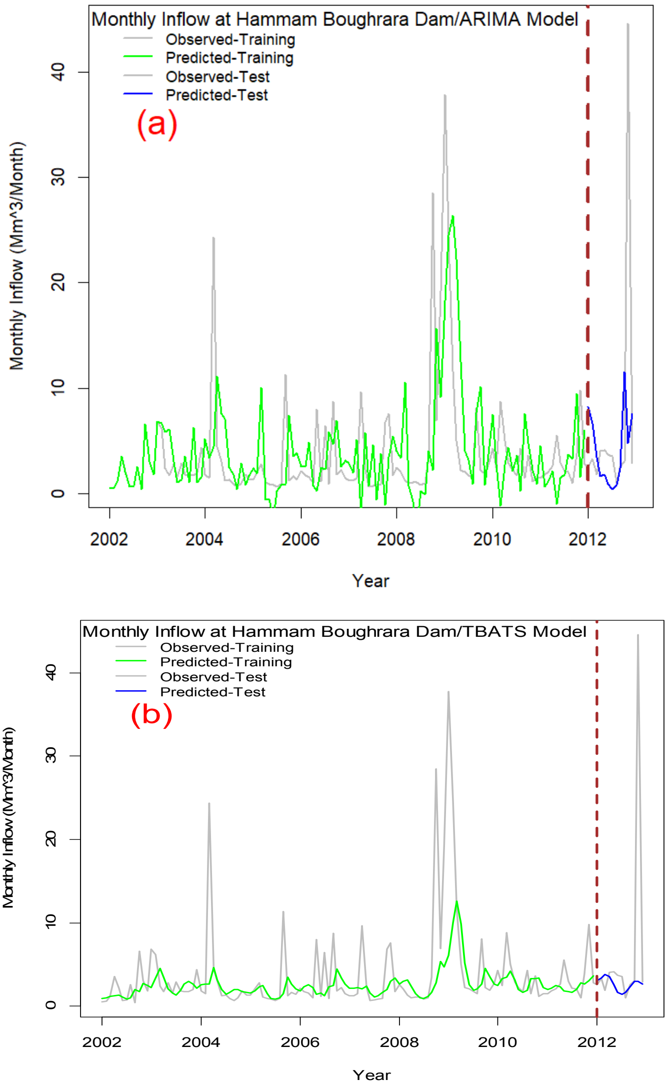
In order to be able to test an ARIMA model on the monthly inflows of the Hammam Boughrara dam (semi-arid case), the sample has been subdivided into a training phase (from 01/01/2002 to 31/12/2011) and a test phase (from 01/01/2012 to 31/12/2012), as previously mentioned.

The auto.arima function (R Core Team, 2021) confronts several models and returns the one that minimises the Akaike Information Criterion, *AIC* (Akaike, 1974): more precision with fewer parameters (principle of parsimony). The application of the ARIMA-type candidate models led to the final result from the optimal model for this purpose, denoted by ARIMA(2,1,0)(3,1,0)[12].

As for the TBATS model, the tbats function (R Core Team, 2021) also compares several different TBATS-type models and in turn arrives at the final result from the corresponding optimal model denoted by TBATS(0, {0,0}, 0.876, {<12,2>}).

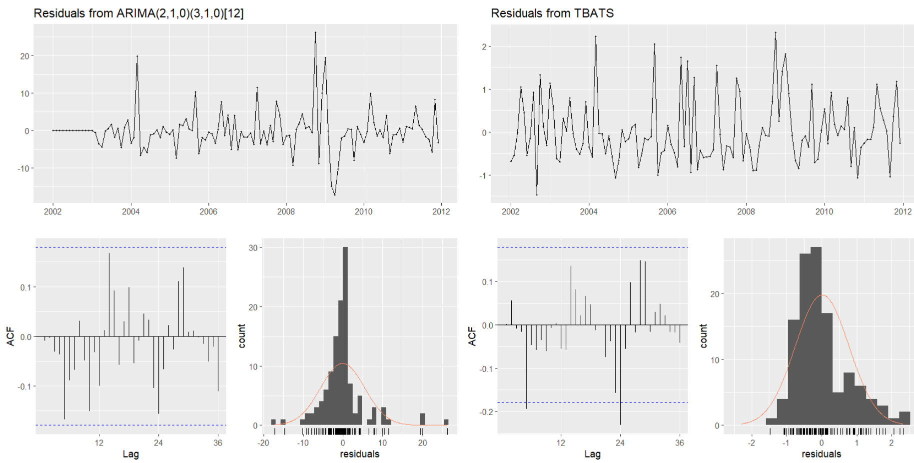
The results of the two ARIMA/TBATS models are shown graphically in Figures 4 and 5, which indicate that the extreme inflows are beyond the scope of the modelling.

Figure 4 Comparison of predicted and measured monthly inflows at the Hammam Boughrara reservoir dam (semi-arid case): (a) ARIMA model and (b) TBATS model (see online version for colours)



The graphs in Figure 5 show that both the ARIMA and TBATS models give forecasts that appear to account for all available information. There is no important autocorrelation in the residual series for the ARIMA model as there appears to be more AR structure for the TBATS model. The histograms look non-normal. Figure 5 also indicates that the residuals from the TBATS(0, {0,0}, 0.876, {<12,2>}) model have a more normal shape than their counterparts from the ARIMA(2,1,0)(3,1,0) [12] model.

Figure 5 Analysis of residuals from ARIMA and TBATS models: Hammam Boughrara dam (semi-arid case) (see online version for colours)



The results summarised in Table 1 indicate that the TBATS(0, {0,0}, 0. 876, {<12,2>}) model for forecasting monthly inflows to the dam of Hammam Boughrara is little different from the ARIMA(2,1,0)(3,1,0)[12] model in terms of *RMSE* values, however it is clearly more efficient than the ARIMA(2,1,0)(3,1,0)[12] model by considering *MAE* and *MAPE* values. Nevertheless, the predictive capacity remains modest (*MAPE* = 39.956%) and the use of more adequate models is strongly recommended for this case study which concerned a region with a semi-arid climate in western Algeria.

Table 1 Results of the application of ARIMA and TBATS models for the monthly inflows at the Hammam Boughrara dam (semi-arid case)

Models	*ARIMA(2,1,0)(3,1,0)[12]*		*TBATS(0, {0,0}, 0.876, {<12,2>})*	
ARIMA(p,d,q)(P,D,Q)$_S$ TBATS	*01/01/2002 to 31/12/2011*	*01/01/2012 to 31/12/2012*	*01/01/2002 to 31/12/2011*	*01/01/2012 to 31/12/2012*
Performance criteria	*Training*	*Test*	*Training*	*Test*
RMSE (Mm^3)	5.520	12.087	5.150	12.056
MAE (Mm^3)	3.281	6.212	2.312	4.303
MAPE (%)	118.299	103.465	58.838	39.956

3.2 Results related to the Subhumid case

The test of an ARIMA model to the series of the monthly inflows of the Beni Haroun dam (subhumid case), also required that its series be subdivided into a training phase (from 01/01/2009 to 31/12/2018) and a test phase (from 01/01/2019 to 31/12/2019). The auto.arima function (R Core Team, 2021) compares several different models and gives the one that minimises the AIC. The application of the competing models leads to the final result which is an optimal model designated by ARIMA(0,1,3)(1,1,0)[12]. Similarly, the function tbats (R Core Team, 2021) confronts distinct TBATS models and turns at the end a model denoted by TBATS(0, {0,1}, –, {<12,2>}).

The results of the temporal growth of the measured and predicted inflows are illustrated graphically in Figure 6 and the examination of the residuals of the selected models are summarised in Figure 7. Figure 6 shows that both the ARIMA and TBATS models reproduce the extreme values of monthly inflows with an acceptable way. The histograms do not appear to be normal.

Figure 6 Comparison of predicted and measured monthly inflows at the Beni Haroun reservoir dam (subhumid case): (a) ARIMA model and (b) TBATS model (see online version for colours)

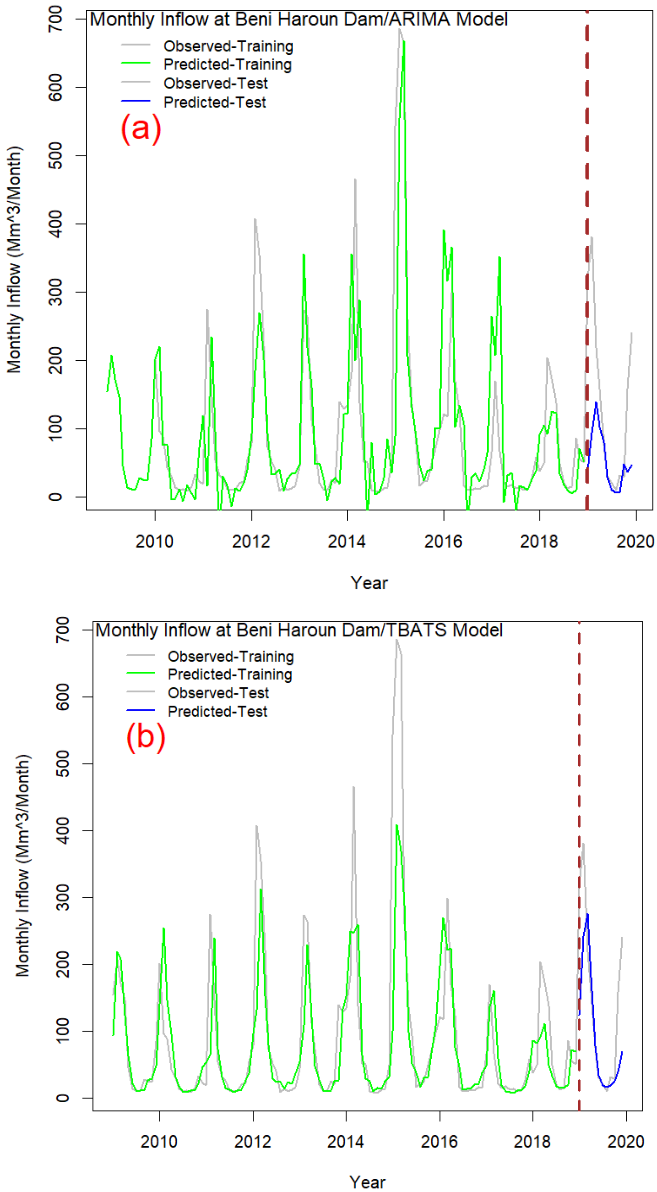
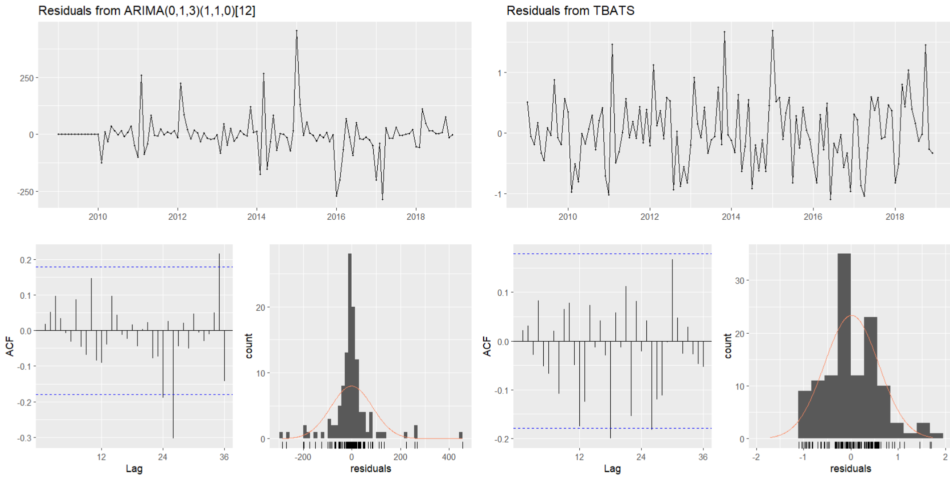


Figure 7 Analysis of residuals from ARIMA and TBATS models: Beni Haroun dam (subhumid case) (see online version for colours)



The results summarised in Table 2 show that the TBATS(0, {0,1}, –, {<12,2>}) model for predicting monthly inflows to the Beni Haroun dam is significantly better than the ARIMA(0,1,3)(1,1,0)[12] model in terms of MAE, RMSE and MAPE values. According to the MAPE value, the predictive capacity of the TBATS(0, {0,1}, –, {<12,2>}) model is still modest (MAPE = 34.786 %) and the seek for other more consistent means of modelling is necessary for this case study which concerned a region characterised by a subhumid climate in the east of Algeria.

Table 2 Results of the application of ARIMA and TBATS models for the monthly inflows at the Beni Haroun dam (subhumid case)

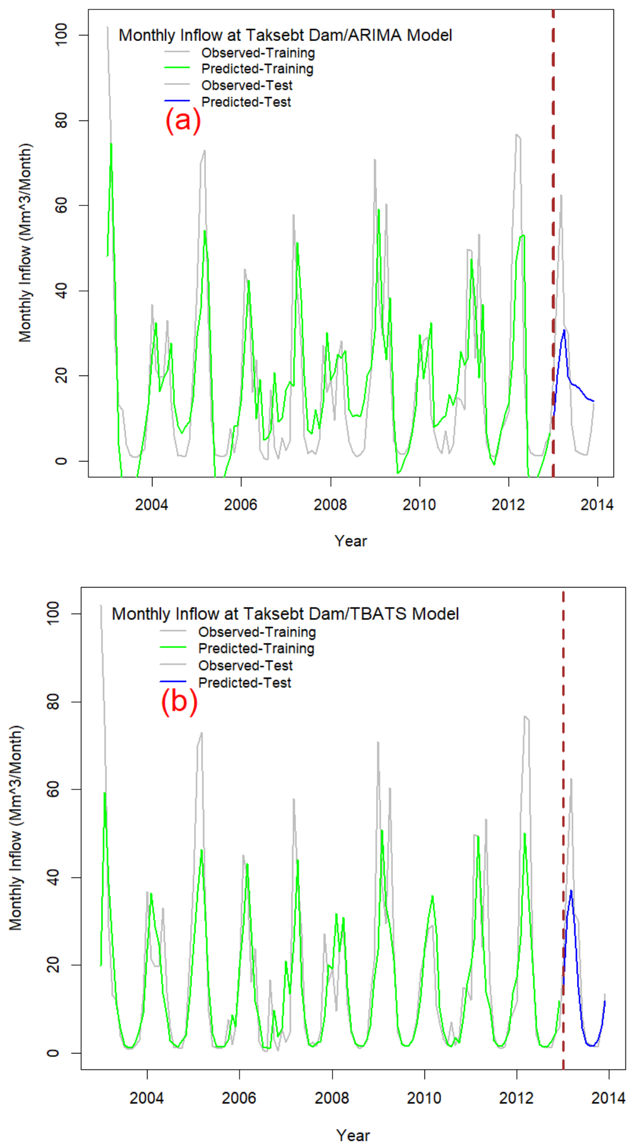
Models	*ARIMA(2,1,0)(3,1,0)[12]*		*TBATS(0, {0,1}, –, {<12,2>})*	
ARIMA(p,d,q)(P,D,Q)$_S$ *TBATS*	*01/01/2002 to 31/12/2011*	*01/01/2012 to 31/12/2012*	*01/01/2002 to 31/12/2011*	*01/01/2012 to 31/12/2012*
Performance criteria	*Training*	*Test*	*Training*	*Test*
RMSE (Mm^3)	84.946	137.145	78.883	93.617
MAE (Mm^3)	45.263	90.383	39.788	61.236
MAPE (%)	94.593	53.204	47.155	34.786

3.3 Results related to the humid case

Finally, the evaluation of the ARIMA model to the series of monthly inflows of the Taksebt dam (humid case), involves the subdivision of the series into a training phase (from 01/01/2003 to 31/12/2012) and a test phase (from 01/01/2013 to 31/12/2013). The auto.arima function (R Core Team, 2021) examines several models and highlights the one that minimises the *AIC*. The application of the various ARIMA models led to the final result denoted by ARIMA(2,0,1)(0,0,1)[12]. The function tbats (R Core Team, 2021) evaluates several typical TBATS models and in turn converges to the optimal result

TBATS(0.032, {0,1}, –, {<12,2>}). The comparison of the measured and the predicted values are given graphically by Figure 8.

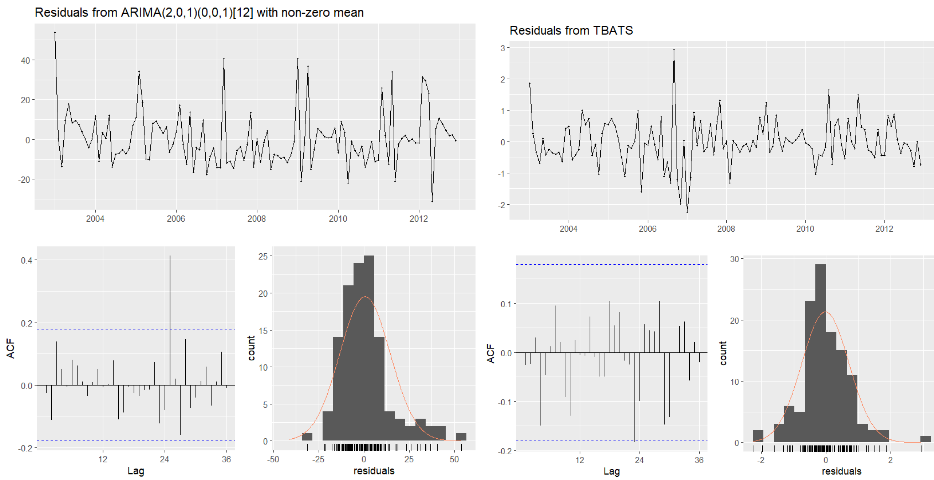
Figure 8 Comparison of predicted and measured monthly inflows at the Taksebt reservoir dam (humid case): (a) ARIMA model and (b) TBATS model (see online version for colours)



The two graphs in Figure 8 show that the two models ARIMA and TBATS just reproduce the monthly inflow peaks in the Taksebt dam, although the temporal evolution (rise/fall) is almost perfect.

The examination of the residuals is summarised in Figure 9 where it is easy to see the almost total absence of significant auto-correlations in the residual series, particularly for the TBATS model. The monthly inflow forecasts for this case study seem very acceptable for the TBATS model, while the ARIMA model should be rejected, especially in terms of MAPE, which exceeds 300%.

Figure 9 Analysis of residuals from ARIMA and TBATS models: Taksebt dam (humid case) (see online version for colours)



The results summarised in Table 3 indicate that the TBATS(0.032, {0,1}, –, {<12,2>}) model for forecasting monthly inflows to the Taksebt dam is very different from the ARIMA(2,0,1)(0,0,1)[12] model in terms of the values of MAE, RMSE and MAPE. The predictive ability is acceptable (MAPE = 29.99%) and the use of more appropriate models is still useful even for this case, which concerned a humid climate in central Algeria.

Table 3 Results of the application of ARIMA and TBATS models for the monthly inflows at the Taksebt dam (humid case)

Models	*ARIMA(2,0,1)(0,0,1)[12]*		*TBATS(0.032, {0,1}, –, {<12,2>})*	
ARIMA(p,d,q)(P,D,Q)$_S$ *TBATS*	*01/01/2003 to 31/12/2012*	*01/01/2013 to 31/12/2013*	*01/01/2003 to 31/12/2012*	*01/01/2013 to 31/12/2013*
Performance criteria	*Training*	*Test*	*Training*	*Test*
RMSE (Mm^3)	13.882	15.638	13.961	9.324
MAE (Mm^3)	9.995	12.963	7.494	5.514
MAPE (%)	201.117	310.551	60.836	29.990

4 Conclusion

In this study, the search for a relatively efficient means of forecasting monthly inflows was completed within three reservoir dams located in distinct climatic regions: Hammam Boughrara dam (semi-arid in western Algeria), Beni Haroun dam (subhumid in eastern Algeria), and Taksebt dam (humid in central Algeria). The models evaluated are among the linear stochastic types well explored in the literature. They are the ARIMA and

TBATS models. The 132-month (11-year) time series are analysed with a single split that exploits the first 120 months (10 years) in the model training phase and the 12 months of the last year will consequently be used for the test of the best ARIMA/TBATS models.

The results of the evaluation of the two models considered show that the ARIMA and TBATS types do not accurately reproduce the variability of monthly inflows during peak periods for the three dams involved in this investigation. The residuals from the adopted models are far from white noise and the auto-correlations in so-called residuals are not completely captured. At the limit the TBATS models may be presented as a remedy to the models which do not take into account the complexity and the dynamicity of the seasonality of the temporal series of the monthly inflows in dams of Algeria in three different climatic regions (semi-arid, subhumid and humid), however, this remedy remains limited in terms of predictive capacity and in the reproduction of the strong extreme values proven by the *MAPE* metric which decreases of 40%, with 35%, and with 30% according to whether (semi-arid, subhumid or humid). The best *MAPE* value has not dropped below 30% which may be still considered as a strong error reflecting the need to use more appropriate models to forecast the monthly inflows in dams of Algeria. The ARIMA models, and in particular TBATS, can ultimately be considered as forecasting tools in preliminary water resource management planning on a monthly scale.

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