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A statistical tool for a hydrometeorological forecast in the lower La Plata Basin

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ABSTRACT

Extreme discharge events in the La Plata Basin need to be prevented. Simple approaches to the forecast problem such as SARIMA models usually predict average values correctly but fail to anticipate extreme events. As an approach to this problem, we used copula methods to model the distribution of the NIÑO 3.4 index and river streamflow pair. We used this to build a six-months forecast for streamflow 95% percentile using observed index values. We added this forecast as an exogenous variable in a SARIMAX model to predict discharge. Given that NIÑO events are usually correlated with extreme discharge events, we expected this model to improve the SARIMA model in predicting extreme events. When comparing both models, we effectively found that SARIMAX model is better than a SARIMA model both for 6- and 12-month discharge forecasts in periods when an El Niño event occurs, while it retains the same performance level when evaluated on all the span of the time series. This model emerges as a lightweight and easily implementable option for decision makers to anticipate extreme events and reduce the negative impacts that they generate.

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KEYWORDS
ENSO; discharge; extreme events; La Plata Basin; forecast; copula methods

1. Introduction

Great floods have occurred in the La Plata Basin in the past, provoking large economic and social damage in the nearby areas, especially affecting the most vulnerable communities (Aparicio-Effen et al., 2016; Báez et al., 2014). In this sense, there is a need to provide different tools for the early identification and prevention of anomaly discharge events (Barros et al., 2020). Moreover, the participation of different scientific communities (climatologists, mathematicians, anthropologists, sociologists, and others) is needed. The generation of tools for decision makers to mitigate negative impacts should be a priority (Bai et al., 2018).

In this work, we propose to study streamflow time series using statistical SARIMAX models that incorporate exogenous variables based on the occurrence of extreme ENSO events. The purpose of this is obtaining a lightweight model that is interpretable and more accurate than traditional approaches for predicting extreme streamflow values.

Different studies (Cai et al., 2020; Cerón et al., 2021; Meis & Llano, 2018 Thielen et al., 2020, among others) have documented the connection between extreme events in the La Plata Basin and ENSO (El Niño Southern Oscillation). Furthermore, in Meis et al. (2020), the authors built a statistical model to quantify the impact from ENSO's behaviour in the seasonal discharge from the Paraná river. These articles indicate that ENSO climatic oscillation may be a relevant variable in hydrological models, particularly for cases when extreme values of streamflow happen. However, none of them quantify if any improvement can be obtained by using ENSO-related variables for the prediction of streamflow series. Instead, the approach taken in Meis et al. (2021) is modelling the joint distribution for the streamflow and ENSO index pair. This work can be seen as a natural continuation of it, as rather than directly adding index values to the models, we build exogenous variables using those joint distributions.

Regarding the usage of statistical models, the authors of Emerton et al. (2019) compare the results from two different models for streamflow, a simple statistical one and a more complex dynamical model. In the results, the authors conclude that there were regions where the dynamical tool considered presented a lesser performance. This was especially true in areas strongly influenced by ENSO, like southern South América. This shows that statistical models can be considered for the streamflow prediction problem, as they are better than complex dynamical models in some scenarios and still offer other advantages. Moreover, that article only considered a very simple statistical model, which we seek to improve in this manuscript.

In this sense, the application of statistical models in climatology and hydrological variables has seen increasing demand in the last decades, in the scientific community as well as in governmental organisms. Although there exist several approaches to this kind of problems, most of them are not easy to interpret, and also some of them involve a great computational implementation cost. For example, deep learning approaches (like the one in Liu et al., 2020) can generally be used to obtain good results at the cost of higher computational cost and lesser interpretability of results. On the other hand, the family of models that we use in this article, which includes the autoregressive moving average model (ARMA), the autoregressive integrated moving average model (ARIMA) from Box and Jenkins (1976) or the seasonal autoregressive moving average model (SARIMA) are models considered to be both understandable and easily implementable.

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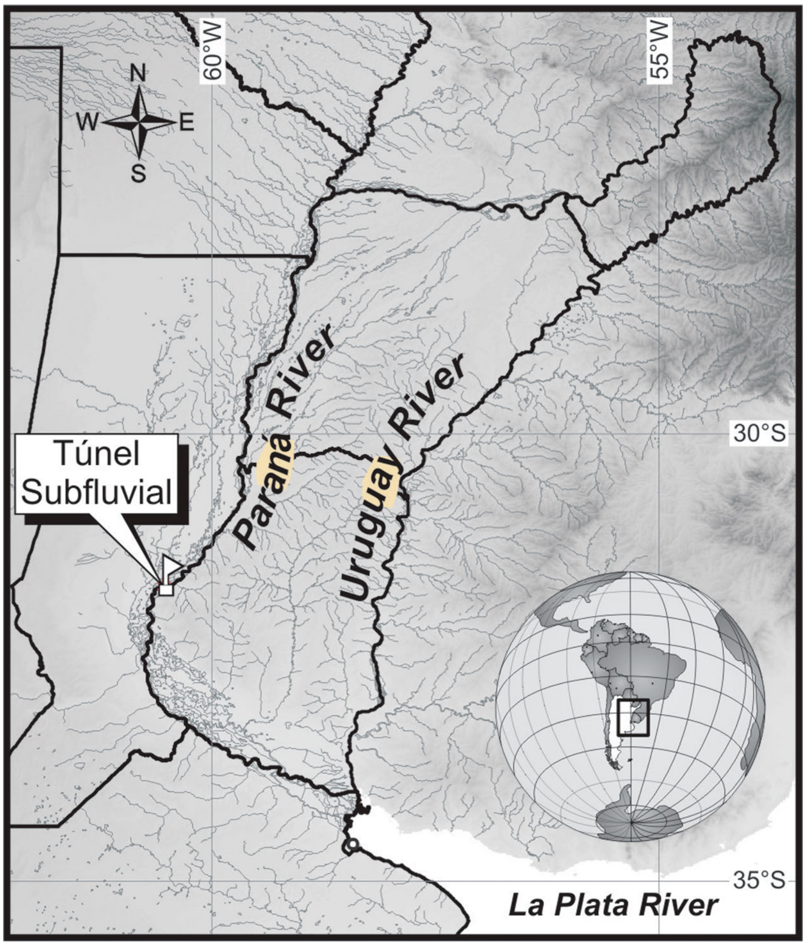


Figure 1. Geographic location of Túnel Subfluvial gauge station.

Regarding the previous discussion, several authors (Adnan et al., 2017; Ahmadpour et al., 2017; Tadesse & Dinka, 2017, and many others) have considered the statistical methodology developed by Box and Jenkins in the study of discharge time series in the past. In those studies, the results for forecasting and modelling discharge were usually considered favourable. These articles only consider a simple autoregressive approach, which we intend to improve in this work by adding exogenous variables.

There are several precedents of using climatic indices as variables on hydrological models in the literature. For instance, the work from Kim et al. (2019) considered climate teleconnections indices to forecast reservoir inflow in South Korea through using SARIMA and SARIMAX, together with more complex artificial intelligence models. The results showed that in some locations time series models exhibited a better performance at forecasting.

In this article, we follow the same idea of incorporating climatic indices to discharge modelling, but we propose a more complex two-step approach. First, we infer what is the expected streamflow given a value for the climatic index using copula methods to model the joint distribution of the two variables (Meis et al., 2021). Then we use the expected streamflow variable obtained in the first step as a regressor variable in a SARIMAX model for streamflow. We show that, compared to a baseline model without exogenous variables, the model obtained by this methodology improves predictive power in case of extreme events while not hurting overall series forecast error. We repeated this for 6-month and 12-month forecasting in the middle Paraná River basin.

2. Data and methodology

For this study, we considered the mean monthly discharge for Túnel Subfluvial gauge station from the Paraná River (Figure 1) in the period 1975–2016. The data were obtained from the Subsecretaría de Recursos Hídricos (Argentine Undersecretariat for Water Resources).

Previous studies have suggested that SARIMA models (Wei, 2005) could be applied to forecast the monthly discharge in the Paraná river (Meis & Llano, 2018) because of their capacity to study time series that do not follow a stationary process (i.e. changes in the mean value, variance or in the autocorrelation structure), as well as time series that present a certain kind of seasonality (periodic fluctuations). The model could be expressed as follows:

$$\Phi_{PS}(B_s)\Phi_p(B)(1-B_S)^D(1-B)^d Z_t = \Theta_{QS}(B_S)\Theta_q(B)u_t \quad (1)$$

Being (p, d, q) parameters for the ordinary part and (P, D, Q) for the seasonal one and S the periodic fluctuation duration, with $u_t \sim N\ (0,\ \sigma^2)$ and $D > 0$ the order of the difference associated with the seasonal part of the model. This model was implemented by Hyndman (2016) in a R package (Package 'forecast').

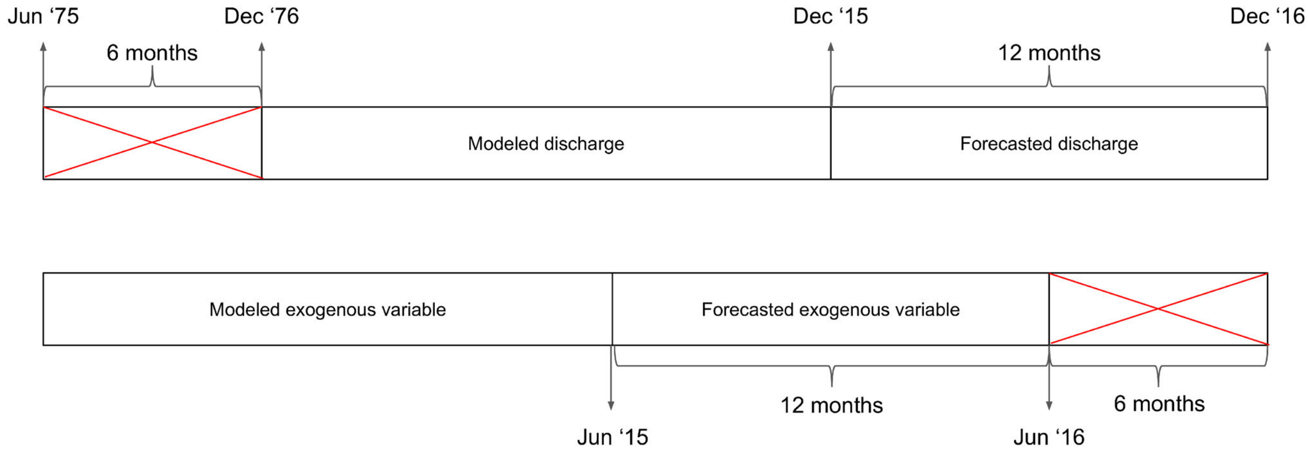


Figure 2. Description of the generation of training and test sets for the discharge mean monthly time series, as well as the exogenous variable. Particular case for 12-month forecast for the series that ends in December 2016. The external variable in the training set corresponds to a discharge expected six months ahead in time.

However, they lack the ability to forecast extraordinary events. In this way, we suggest that this could be improved by considering an external variable. As the aim of this work was to see the improvement of a certain external variable in a SARIMA model, first, we considered the simple approach already used, but with an extended grid. Therefore, we ran a grid search over the hyperparameters, in which we considered values for p and q less than or equal to four and P and Q less than or equal to one, analysing a total of 100 possible hyperparameter combinations. However, we must clarify that we sought to obtain a parsimonious (simpler) model, so we kept that in consideration at the time of analysing grid search results.

In the process of building the best possible model for the time series, we considered identification methods (autocorrelation function (ACF), partial autocorrelation (PACF)), estimation of the parameters of the SARIMA model and diagnosis methods. In this process, the residual analysis was carried out with different techniques (ACF, PACF) as well as with statistical tests like the Ljung–Box, which consider that the data are distributed in an independent way as a null hypothesis. For the selection model, we used a

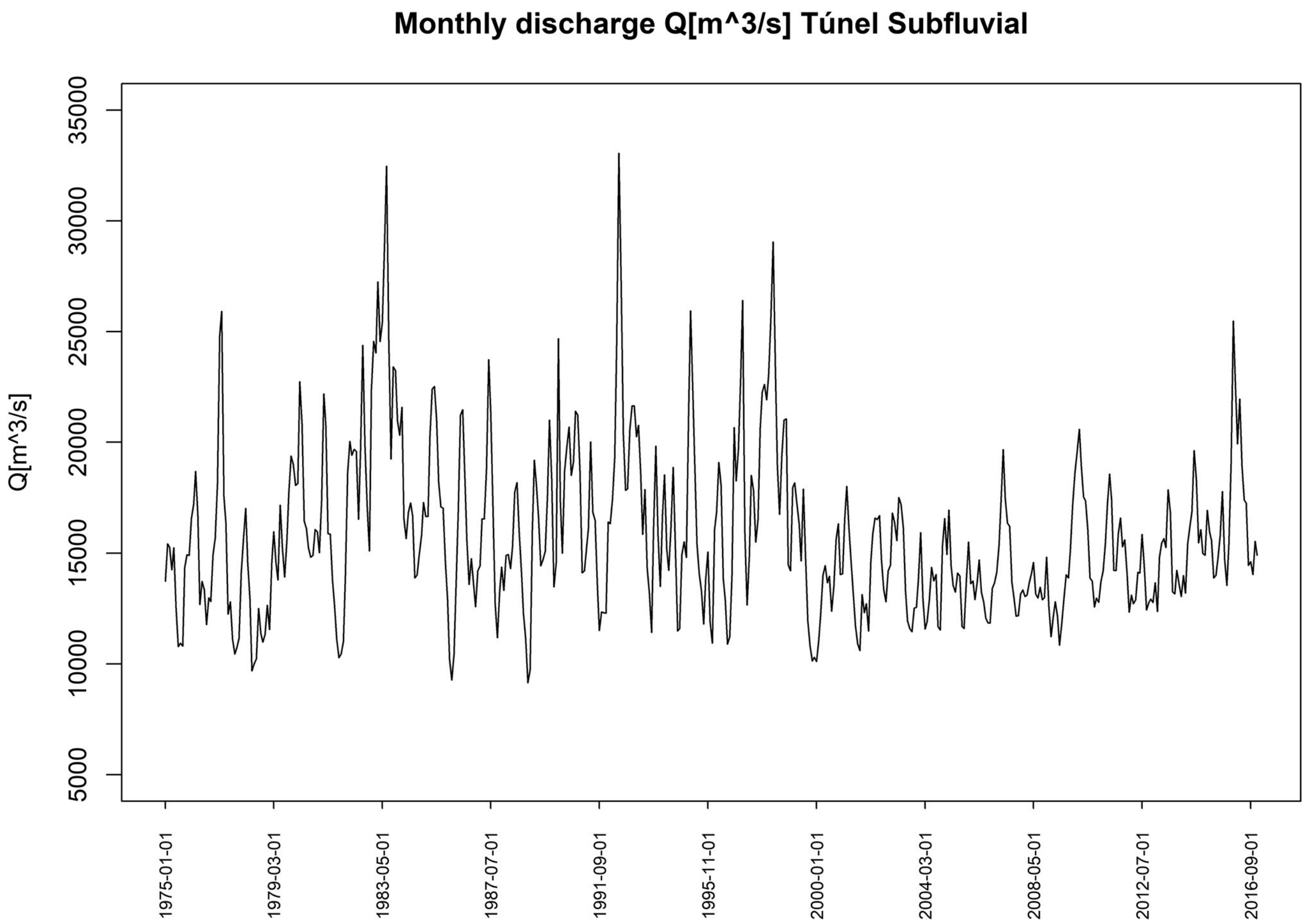


Figure 3. Mean monthly discharge time series for Túnel Subfluvial in the period 1975–2015.

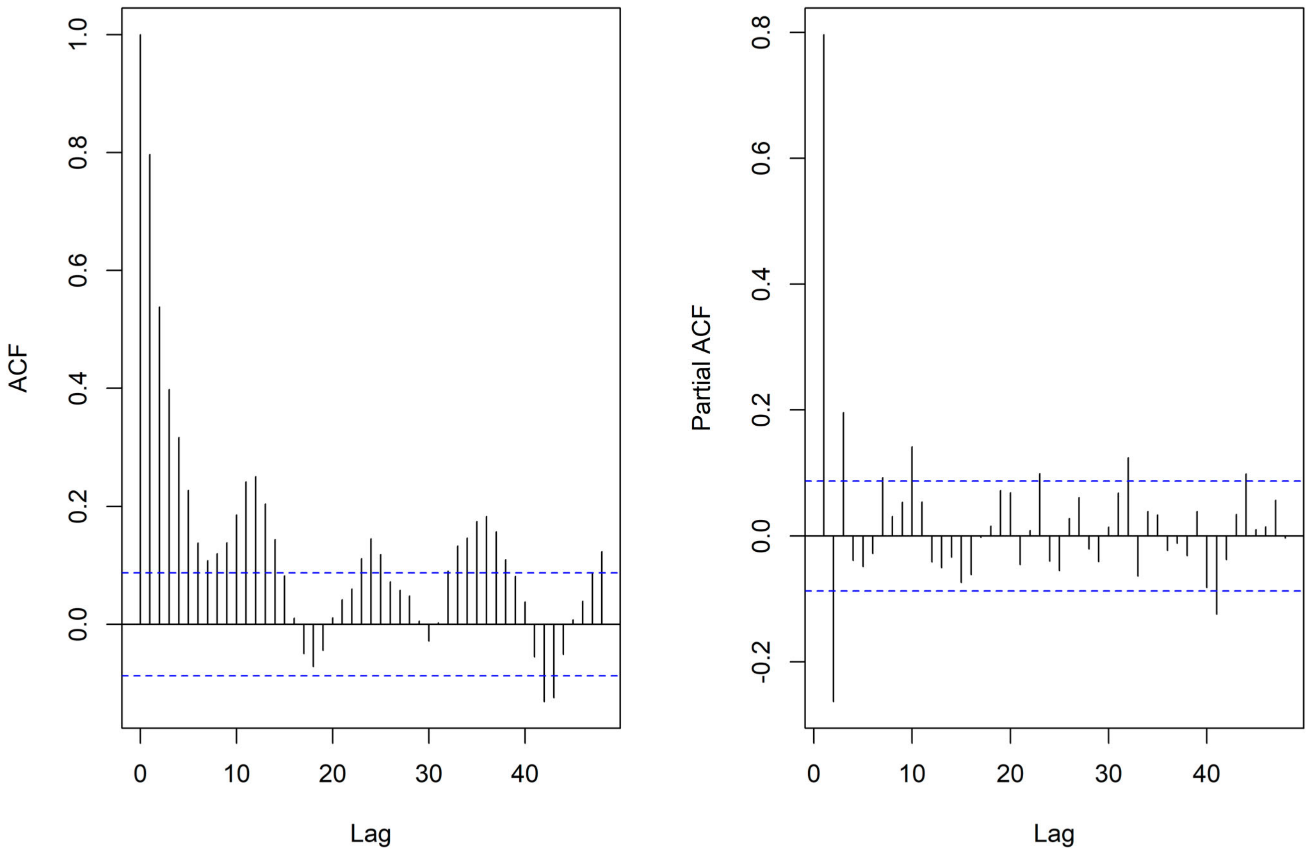


Figure 4. ACF (left) and PACF (right) from Túnel Subfluvial mean monthly time series from the period 1975–2015.

compromise between ACF, PACF and the Ljung–Box. Furthermore, we took into account two metrics: the Akaike criterion (AIC) and the efficiency coefficient model Nash–Sutcliffe (NSE). This latter index is always minor to one, where values closer to one represent adequate models, while negative values exhibit a poor performance.

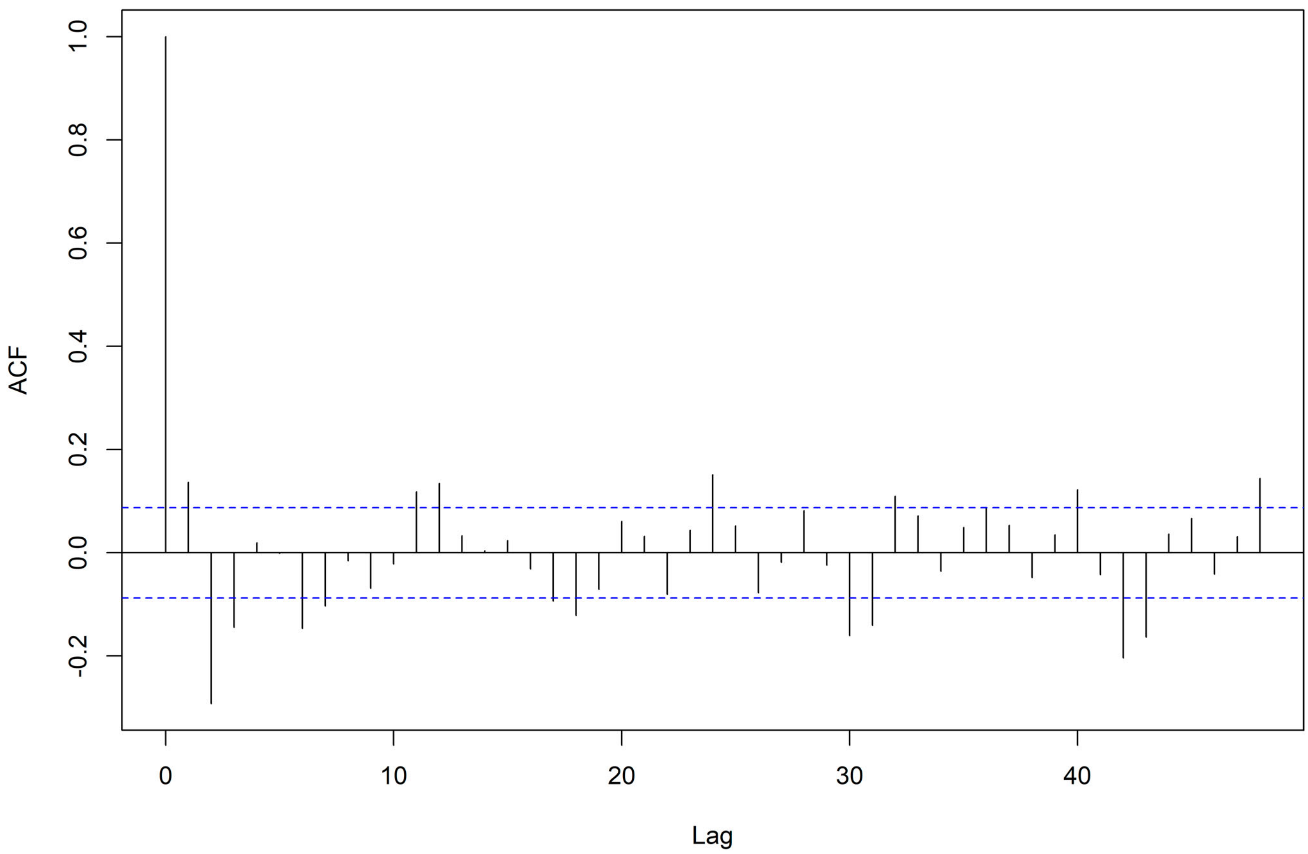


Figure 5. ACF for the differentiated mean monthly time series from Túnel Subfluvial gauge station corresponding to the period 1975–2015.

Table 1. AIC, NSE for the 100 SARIMA model hyperparameters combination for the mean monthly discharge in Túnel Subfluvial gauge station for the period 1975–2015.

	p	Q	P	Q	AIC	NSE
1	0	0	0	0	9443.58	−0.46
2	1	0	0	0	9027.56	0.39
3	2	0	0	0	9006.55	0.42
4	3	0	0	0	8983.57	0.45
5	4	0	0	0	8985.41	0.45
6	0	1	0	0	9106.43	0.28
7	1	1	0	0	8992.40	0.43
8	2	1	0	0	8993.10	0.44
9	3	1	0	0	8985.46	0.45
10	4	1	0	0	8987.30	0.45
11	0	2	0	0	9026.42	0.39
12	1	2	0	0	8990.72	0.44
13	2	2	0	0	8991.41	0.44
14	3	2	0	0	8986.40	0.45
15	4	2	0	0	8964.34	0.48
16	0	3	0	0	9010.57	0.42
17	1	3	0	0	8989.87	0.44
18	2	3	0	0	8991.34	0.44
19	3	3	0	0	8970.56	0.47
20	4	3	0	0	8933.68	0.52
21	0	4	0	0	9007.89	0.42
22	1	4	0	0	8989.74	0.45
23	2	4	0	0	8993.87	0.44
24	3	4	0	0	8943.27	0.51
25	4	4	0	0	8953.44	0.50
26	0	0	1	0	9349.17	−0.19
27	1	0	1	0	8893.87	0.54
28	2	0	1	0	8872.20	0.57
29	3	0	1	0	8858.01	0.58
30	4	0	1	0	8859.30	0.58
31	0	1	1	0	9002.03	0.43
32	1	1	1	0	8862.45	0.57
33	2	1	1	0	8863.53	0.57
34	3	1	1	0	8859.39	0.58
35	4	1	1	0	8862.01	0.58
36	0	2	1	0	8911.20	0.53
37	1	2	1	0	8862.44	0.58
38	2	2	1	0	8862.67	0.58
39	3	2	1	0	8857.38	0.59
40	4	2	1	0	8852.45	0.59
41	0	3	1	0	8884.03	0.56
42	1	3	1	0	8861.54	0.58
43	2	3	1	0	8863.53	0.58
44	3	3	1	0	8856.79	0.59
45	4	3	1	0	8852.98	0.59
46	0	4	1	0	8881.42	0.56
47	1	4	1	0	8863.51	0.58
48	2	4	1	0	8855.90	0.59
49	3	4	1	0	8837.07	0.61
50	4	4	1	0	8854.17	0.59
51	0	0	0	1	9242.71	0.07
52	1	0	0	1	8763.79	0.67
53	2	0	0	1	8738.63	0.68
54	**3**	**0**	**0**	**1**	**8721.42**	**0.70**
55	4	0	0	1	8722.89	0.70
56	0	1	0	1	8887.32	0.56
57	1	1	0	1	8726.84	0.69
58	2	1	0	1	8728.22	0.69
59	3	1	0	1	8722.95	0.70
60	4	1	0	1	8724.88	0.70
61	0	2	0	1	8781.88	0.65
62	1	2	0	1	8727.36	0.69
63	2	2	0	1	8725.37	0.70
64	3	2	0	1	8724.75	0.70
65	4	2	0	1	8726.57	0.70
66	0	3	0	1	8752.54	0.68
67	1	3	0	1	8724.19	0.70
68	2	3	0	1	8725.95	0.70
69	3	3	0	1	8724.38	0.70
70	4	3	0	1	8727.56	0.70
71	0	4	0	1	8748.44	0.68
72	1	4	0	1	8725.75	0.70
73	2	4	0	1	8727.21	0.70
74	3	4	0	1	8724.81	0.70
75	4	4	0	1	8726.17	0.70
76	0	0	1	1	9239.99	0.08
77	1	0	1	1	8765.47	0.67
78	2	0	1	1	8740.46	0.69
79	3	0	1	1	8722.58	0.70
80	4	0	1	1	8724.12	0.70
81	0	1	1	1	8884.60	0.57
82	1	1	1	1	8728.39	0.70
83	2	1	1	1	8729.70	0.70
84	3	1	1	1	8724.19	0.70
85	4	1	1	1	8726.10	0.70
86	0	2	1	1	8781.89	0.66
87	1	2	1	1	8728.71	0.70
88	2	2	1	1	8727.07	0.70
89	3	2	1	1	8725.93	0.70
90	4	2	1	1	8728.18	0.70
91	0	3	1	1	8753.90	0.68
92	1	3	1	1	8725.61	0.70
93	2	3	1	1	8727.48	0.70
94	3	3	1	1	8727.07	0.70
95	4	3	1	1	8729.43	0.70
96	0	4	1	1	8749.85	0.68
97	1	4	1	1	8727.36	0.70
98	2	4	1	1	8728.80	0.70
99	3	4	1	1	8725.26	0.71
100	4	4	1	1	–	–

In bold it is the SARIMA(3, 0, 0)(0, 1, 1)$_{12}$.

Furthermore, for the selection of the hyperparameters for the model we took into account two metrics: the Akaike criterion (AIC) and the efficiency coefficient model Nash Sutcliffe (NSE). This latter index is always minor to one, where values closer to one represent adequate models, while negative values exhibit a poor performance.

After the model selection, two forecasts were generated. First, for the monthly discharge, we forecasted the period July 2016 to December 2016 (six months) with a training period 1975 to June 2016. Second, a 12-month forecast for the period January 2016 to December 2016 with the training period 1975–2015 was done. We applied the algorithm implemented by Stoffer (2016) (2).

$$\Phi_{PS}(B_s)\Phi_p(B)(1-B_S)^D(1-B)^d Z_{t+1} = \Theta_{QS}(B_S)\Theta_q(B)u_{t+1} \quad (2)$$

After obtaining the results for the initial SARIMA approach, we considered the model obtained by incorporating an expected discharge variable as an exogenous variable to the SARIMA model with the already selected hyperparameters (Xie et al., 2013), in order to evaluate the value it adds to the predictive task (3).

$$\Phi_{PS}(B_s)\Phi_p(B)(1-B_S)^D(1-B)^d Z_t = \Theta_{QS}(B_S)\Theta_q(B)u_t + \sum_{h=0}^{b}\beta_h X_{t-h} \quad (3)$$

with $u_t \sim N(0, \sigma^2)$, and $D > 0$ the difference order associated with the seasonal part of the model, X_t is the external variable.

In a previous work, we have estimated the mean expected discharge given a NIÑO 3.4 value from six months earlier. This variable was obtained from a joint distribution between the shifted index and the discharge, which was estimated through a copula method (Meis et al., 2020). In this last research, we proposed a way to generate conditional samples from the variable Y (discharge) given observations from the variable X (index). This process consists in the following:

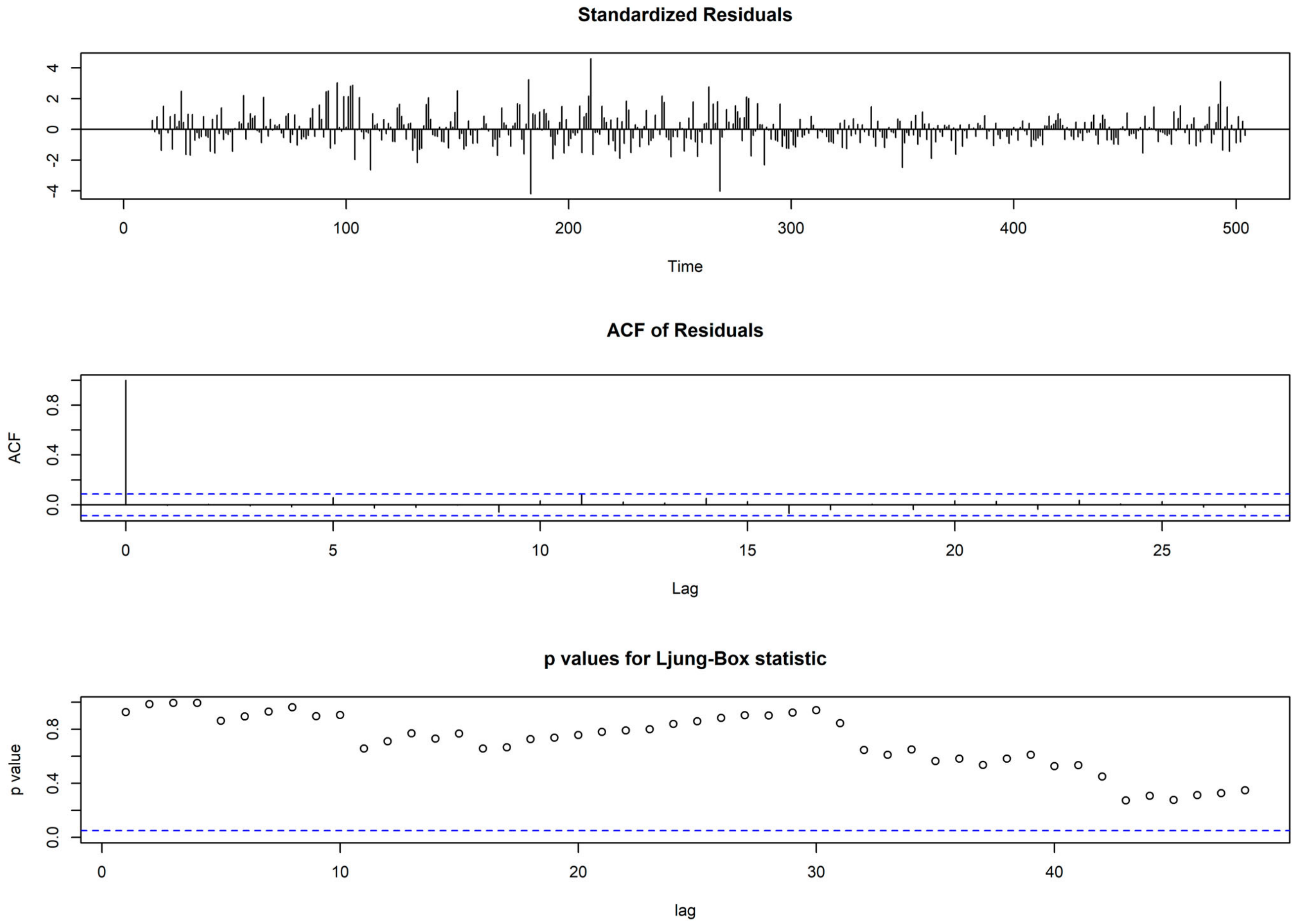


Figure 6. ACF, and standardized residual Túnel Subfluvial time series together with the Ljung Box *p*-values for the training period 1975–2015.

(1) Transform X and Y to uniform variables by applying the inverse of their cumulative distribution function. Obtain $U_1 = F^{-1}{}_x(X)$ and $U_2 = F^{-1}{}_Y(Y)$ uniform variables and name $u_1 = F^{-1}{}_X(x)$ the observed value from U_1 corresponding to x, the observed value from X.
(2) Obtain a conditional sample u_2 from U_2 given $U_1 = u_1$ using the conditional function distribution from the copula (4).
(3) Transform the uniform sample u_2 to the space of the original variable Y applying F_Y, thus obtaining a sampled value $y = F_Y(u_2)$.

For this procedure, we carried out the implementation proposed by Schepsmeier et al. (2018).

$$C(u_2|u_1) = P(U_2 \leq u_2|U_1 = u_1) = \frac{\partial C(u_1, u_2)}{\partial u_1} \quad (4)$$

We have already demonstrated that the new six-month expected discharge variable could be useful to forecast extreme events (Meis et al., 2021). However, we should notice that the discharge variable was obtained quarterly, while in this present research, we evaluated a monthly model. We converted the quarterly variable into a monthly one by repeating the same value for each month in the same trimester and then applying a moving average of order three to this new time series.

Once we got the SARIMA and SARIMAX models, we did the cross-validation in the time series in order to compare the univariate model with the one that included the exogenous variable. For this, the time series was truncated at 200 different points (beginning with the whole series and discarding one month). At each point, the truncated series was used as a training set, and the following 6 or 12 months as a testing set, as it is observed in Figure 2.

We proceeded to forecast values for the test set from the model fit with the training set and the external variable corresponding to the tested period. For each split, we computed the mean squared error in the test set for the model with and without the exogenous variable. Finally, we computed the average relative difference between both errors, where negative values imply that the SARIMAX model presents a better performance.

It is important to say that as the exogenous variable presented the last value in the third trimester of 2016, we decided to do the validation until September 2016.

3. Results

The monthly discharge time series from Túnel Subfluvial gauge station for the period 1975–2016 is shown in Figure 3. In this figure, it is possible to highlight that there is a higher number of extreme events during the first 20 years. Particularly, we can see three extreme events with values of discharge over 30,000 m^3/s in that period related to ENSO events (Antico et al., 2016). Even more, we could see that the discharge variable had shown no homoscedasticity since the last 20 years. This could be related to an external human-manipulation variability such as the operation of a dam. However, we need to highlight that we are interested in the discharge variability forecast related to a natural external

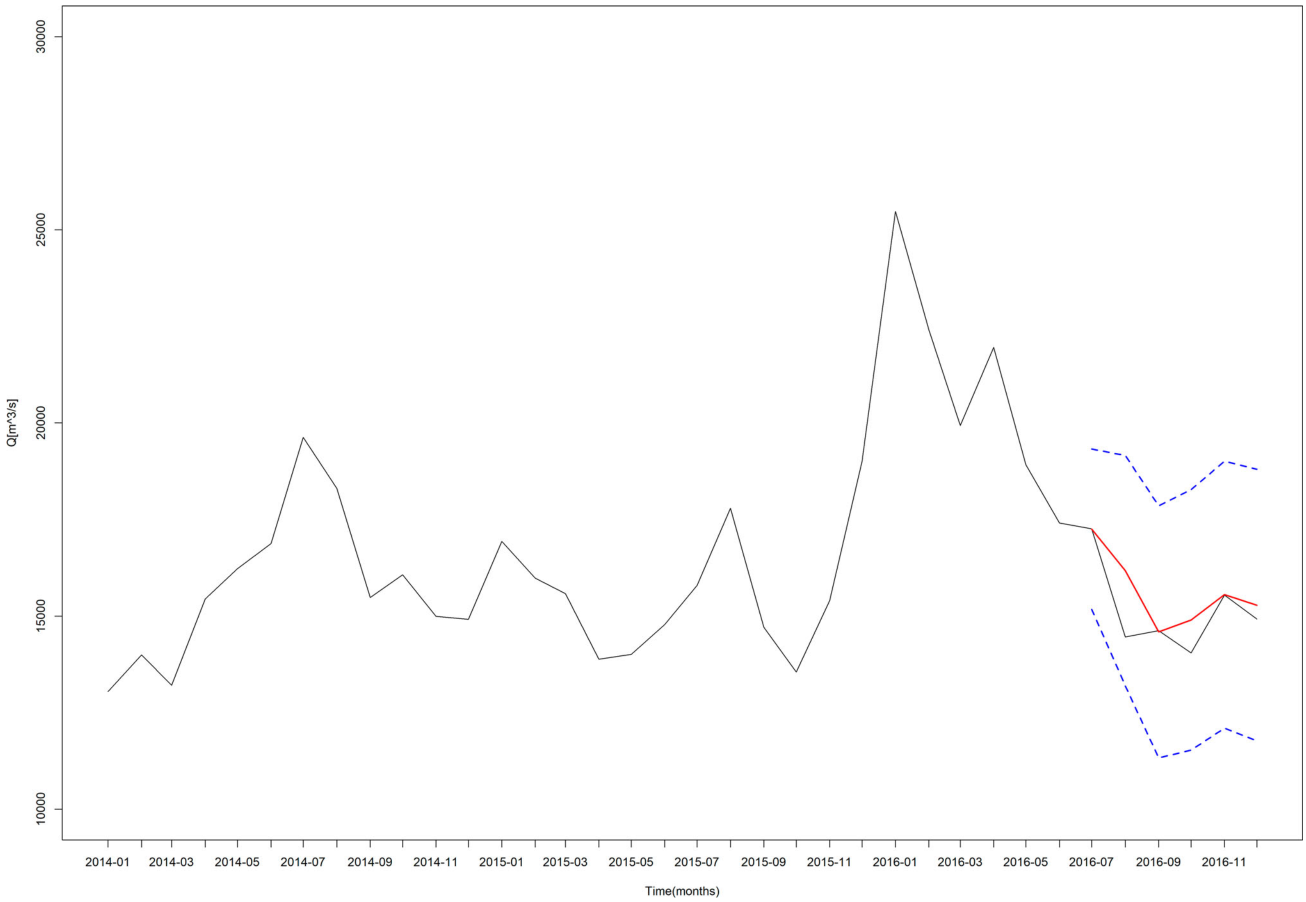


Figure 7. Six months forecast for the discharge from Túnel Subfluvial. The red line is the forecast from the SARIMA model, the black line is observed data, the blue lines represent one-standard deviation from the forecast.

forcing. Furthermore, the time series presented seasonality and stationarity (Meis & Llano, 2018, 2019) where the seasonality is shown in the form of an annual wave, with the maximum monthly mean between March and April, and the minimum around September. This can be seen in Figure 3. As for stationarity, we found in Meis and Llano (2018) and Meis et al. (2021) that the time series considered were stationary, as no trend was found in the last 40 years.

As it was noticed in the previous section, we extended the grid search applied in a previous work over the hyperparameters, in which we considered values for p and q less than or equal to four and P and Q less than or equal to one, analysing a total of 100 possible hyperparameter combinations. The autocorrelation and partial autocorrelation functions for the monthly discharge from Túnel Subfluvial gauge station together with the confidence interval for what is produced by white noise (95% of confidence, dot lines) are shown in Figure 4.

From the ACF (Figure 4, left), we could notice that lags multiple of 12 presented a high and significant correlation, in line with results from the previous work. Even more, the seasonality of the series could be observed by differentiating the time series once, this can be seen in Figure 5 where seasonality could be easily distinguished from the ACF. Furthermore, it is possible to observe that lag three is significant in the partial autocorrelation function (Figure 4, right). This could be an indicator that the hyperparameter p for the SARIMA model could be of order three.

As it has been mentioned in the methodology section, in the hyperparameter grid search for the SARIMA model we considered values of the parameters p and q between 0 and 4, and P and Q between 0 and 1. This gave us 100 possible combinations of hyperparameters. We picked the hyperparameter combination with minimum AIC and maximum NSE values, which turned out to be SARIMA$(3, 0, 0)(0, 1, 1)_{12}$ for the two training periods mentioned in the methodology section.

In Table 1, we show the AIC values for the different hyperparameter combinations, together with the NSE coefficient for training period (1975–06/2016). The selected combination presented an AIC equal to 8721.42, while the NSE value was equal to 0.70. This means that the selection of the hyperparameters considered might be adequate. For the second training period, the values obtained were similar (results not shown).

In Figure 6, we exhibit standardized residuals (above), ACF (middle) and the result from the Ljung–Box test applied to the residuals from the model for the selected combination of parameters (below), and in the Ljung Box test, the null hypothesis was not rejected for all the lags considered. From these results, it is easy to observe that the hyperparameter selection was adequate.

3.1. Six and 12 month forecast ahead for the discharge from Túnel Subfluvial gauge station

We carried out forecasts for the last 6 and 12 months of the time series using the SARIMA model selected in the previous section. The prediction together with the original series and the classical one-standard deviation from the forecast (confidence interval) are shown in Figures 7 and 8. It is possible to

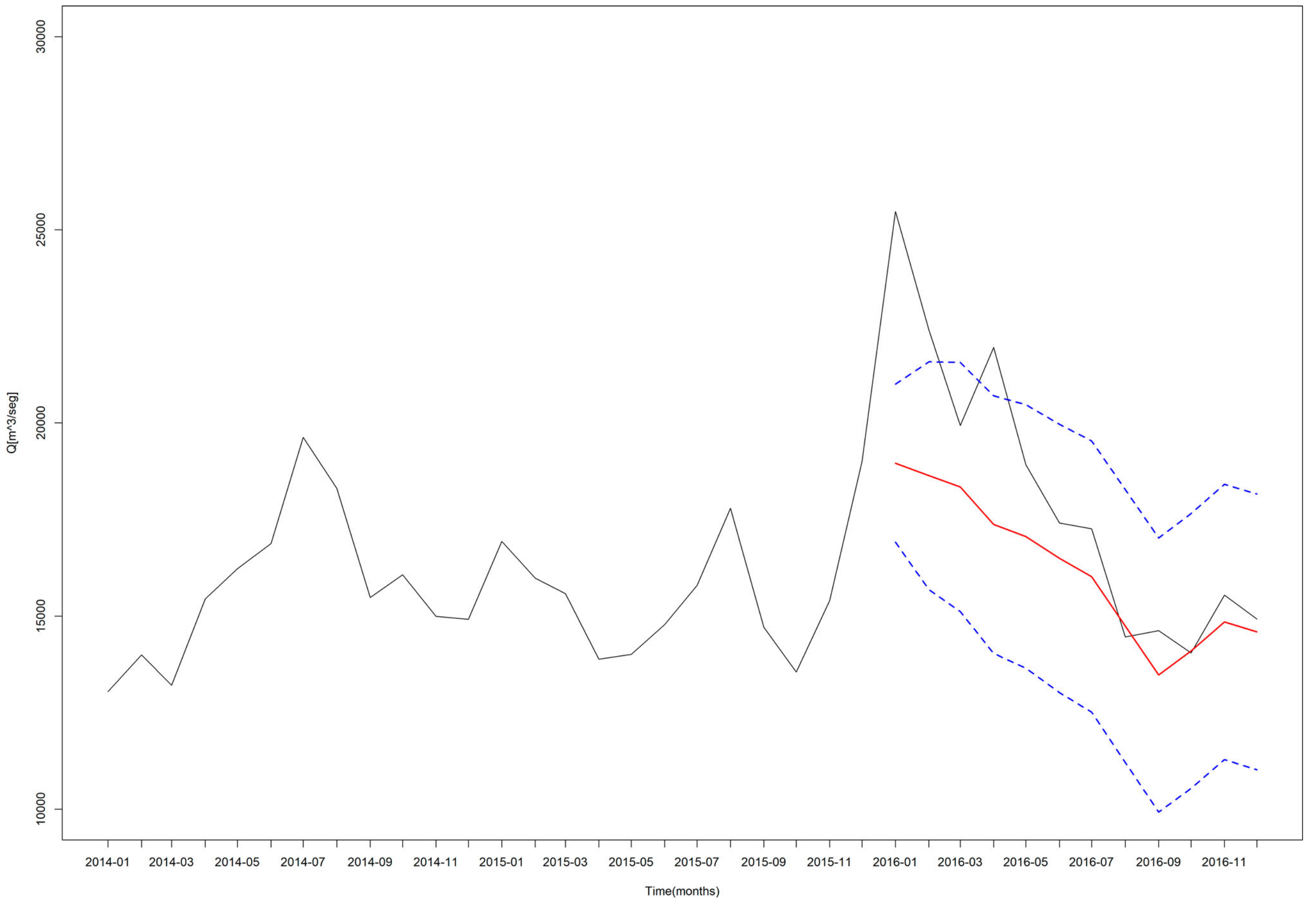


Figure 8. Twelve-month forecast for the discharge from Túnel Subfluvial. The red line is the forecast from the SARIMA model, the black line is observed data, the blue lines represent one-standard deviation from the forecast.

observe in those figures that although the actual series for six months lies inside the confidence interval generated by the model, the location of the minimum points is not properly obtained. On the other hand, in the 12-month forecast it is important to highlight the overestimation of the maximum values for January and April for 2016.

As the last results for the 12-month forecast presented an underestimation of the streamflow in the first months, possibly, associated with the influence of the ENSO phenomenon, as 2015–2016 was considered an El Niño event, we proposed incorporating the expected discharge estimated from a copula method as an exogenous variable for the SARIMA model, as described in the methodology section. As we have already analyzed in a previous work by Meis et al. (2021), we obtain a copula of the Joe family when fitting a joint distribution for discharge and index. This can be seen in Equation (3). As mentioned in methodology, we carried out a comparison between the model without the external variable and the SARIMAX model, through the computation of the mean squared error of 200 truncated time series, in cross-validation fashion. We measured the error in the forecast for 12 months as well as for six months at each step. We obtained that for the 12-month forecast, the SARIMAX model was 2.44% worse than the univariate model, while for the six-month forecast it turned out to be 1% better.

However, it is interesting to highlight that although on average the incorporation of the exogenous variable seems not to improve the model, we noticed large differences when forecasting extreme events.

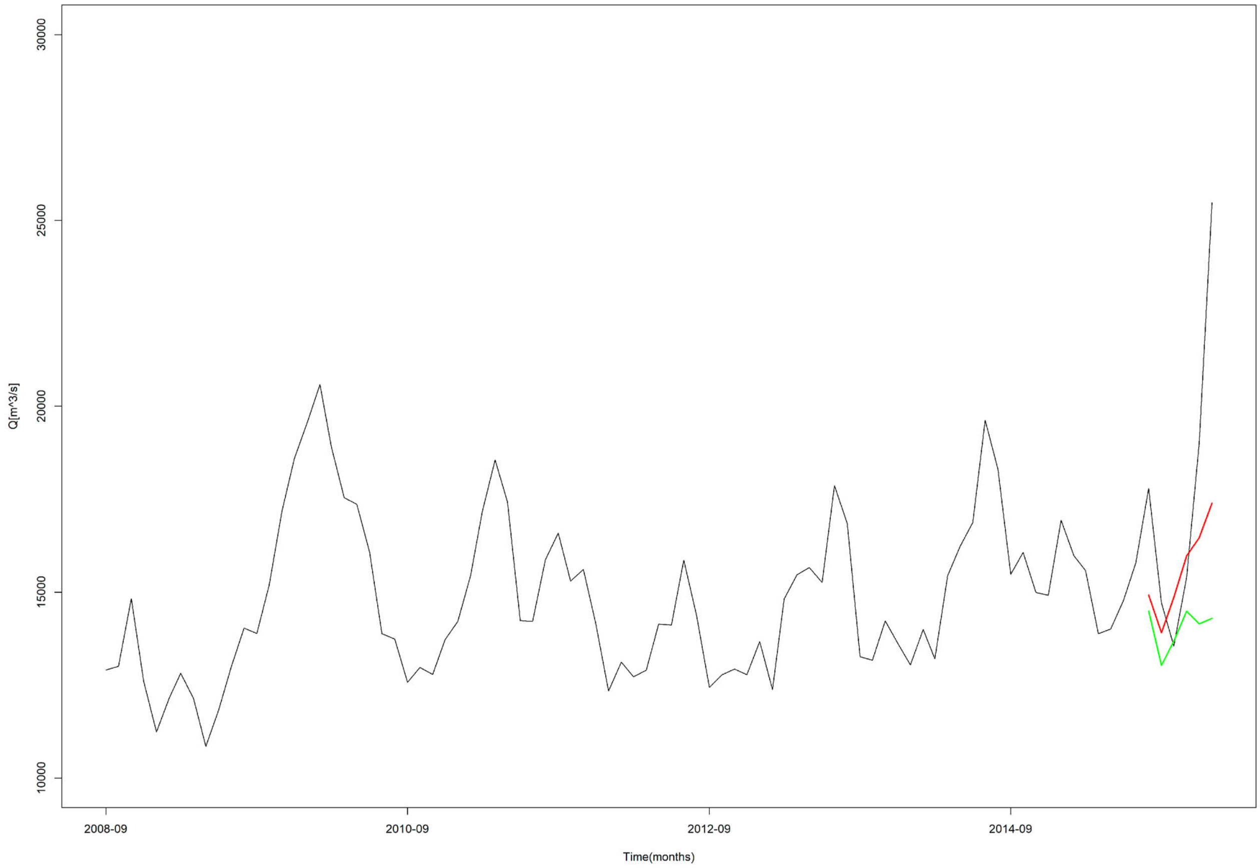
To evidence this phenomenon, we report the relative performance of the model SARIMAX with respect to the univariate in the first 12 iterations of the cross-validation, corresponding to the prediction of the period that finalized during October 2015 to September 2016, in which the test

Table 2. Percentual mean squared error for the six-month forecast model from Túnel Subfluvial gauge station.

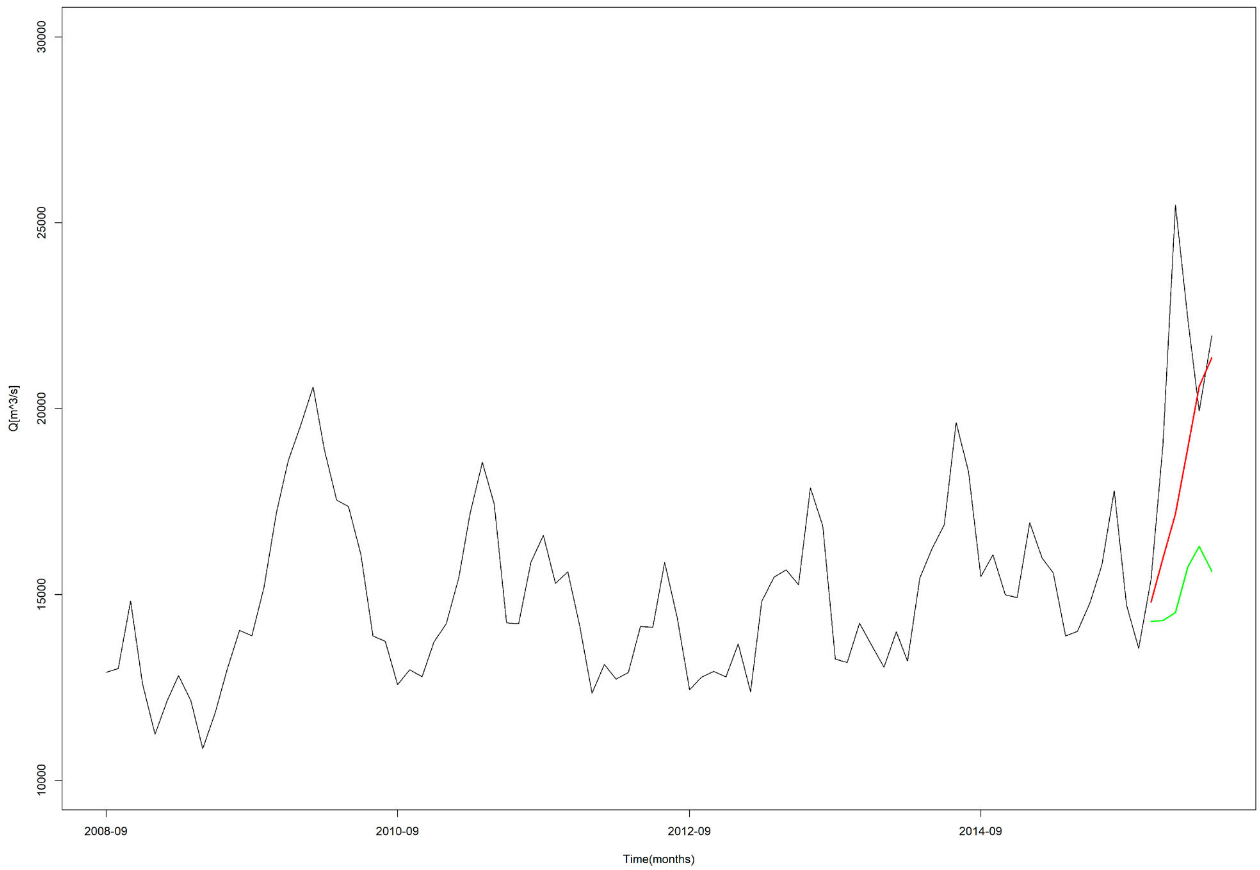
End tested date	Six months
September 2016	74.79%
August 2016	68.42%
July 2016	65.75%
June 2016	−0.54%
May 2016	−50.22%
April 2016	−62.57%
March 2016	−51.22%
February 2016	−38.48%
January 2016	−40.4%
December 2015	−61.29%
November 2015	−47.55%
October 2015	−46.45%

Table 3. Percentual mean squared error for the 12-month forecast model from Túnel Subfluvial gauge station.

End tested date	Twelve months
September 2016	−9.86%
August 2016	−9.37%
July 2016	−11.89%
June 2016	−13.04%
May 2016	−12.97%
April 2016	−12.76%
March 2016	−11.46%
February 2016	−10.99%
January 2016	−8.29%
December 2015	−11.46%
November 2015	−10.99%
October 2015	−8.29%

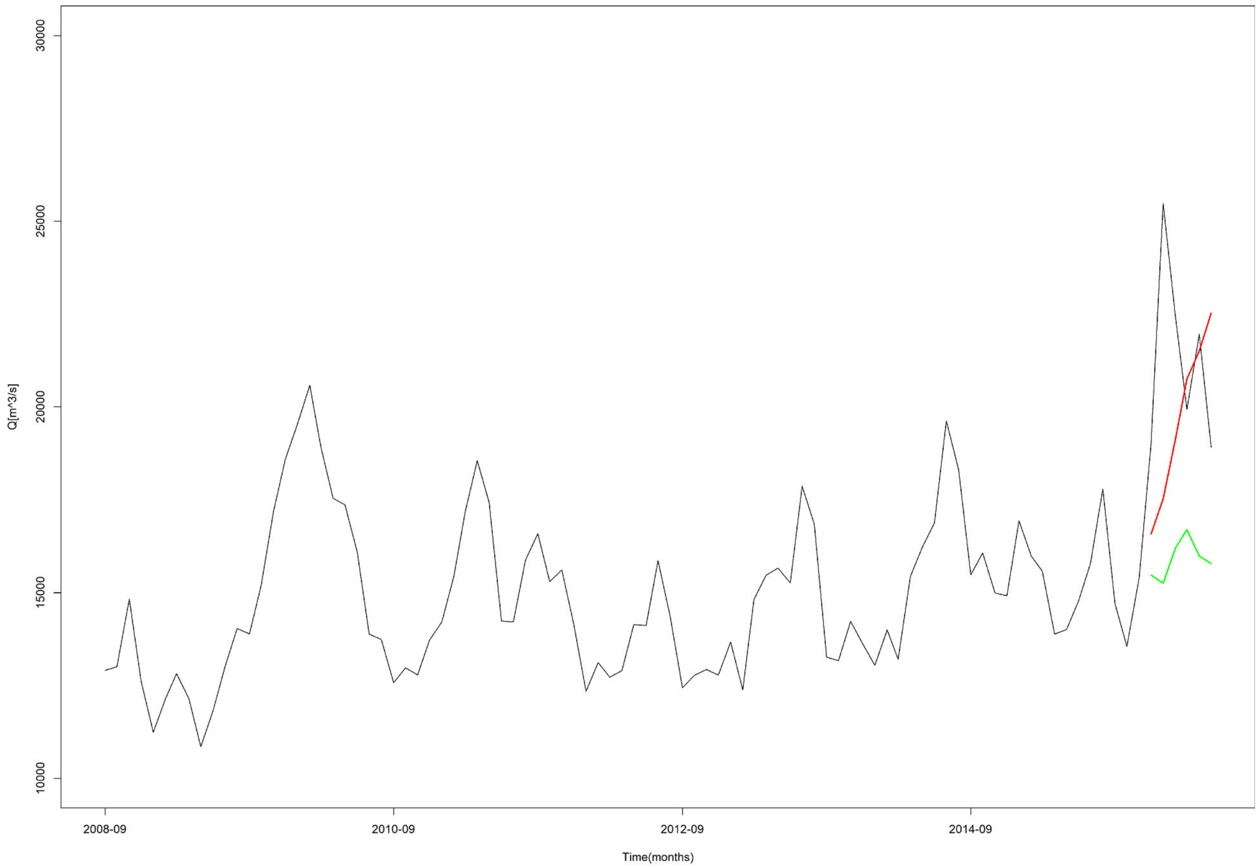


(a)

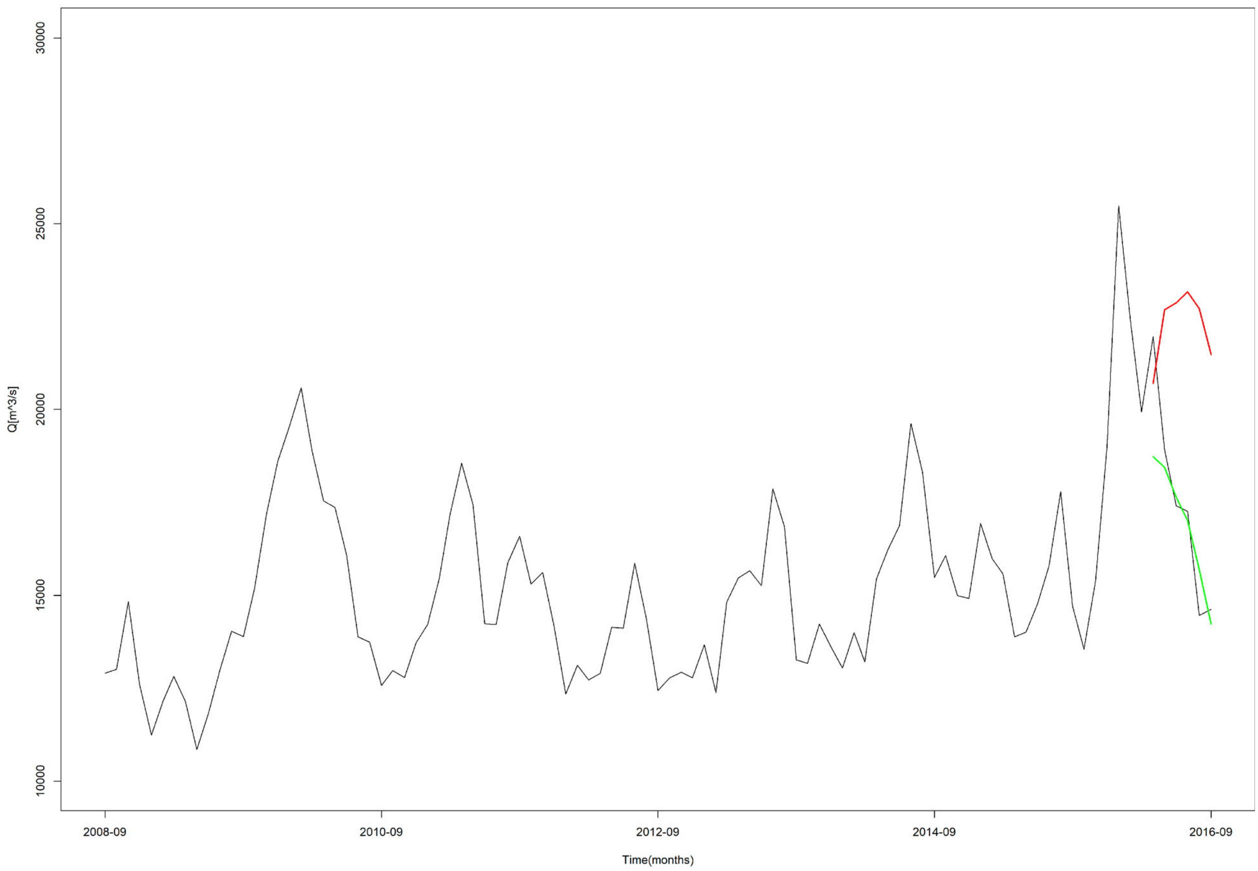


(b)

Figure 9. Examples of the six-month forecast for monthly discharge in Túnel Subfluvial gauge station from October 2015 to September 2016. The red line represents the model that includes the exogenous variable, the green line represents the SARIMA without exogenous variable. (a) End tested December'15, (b) End tested April'16, (c) End tested May'16, (d) End tested September'16.



(c)



(d)

Figure 9 *Continued*

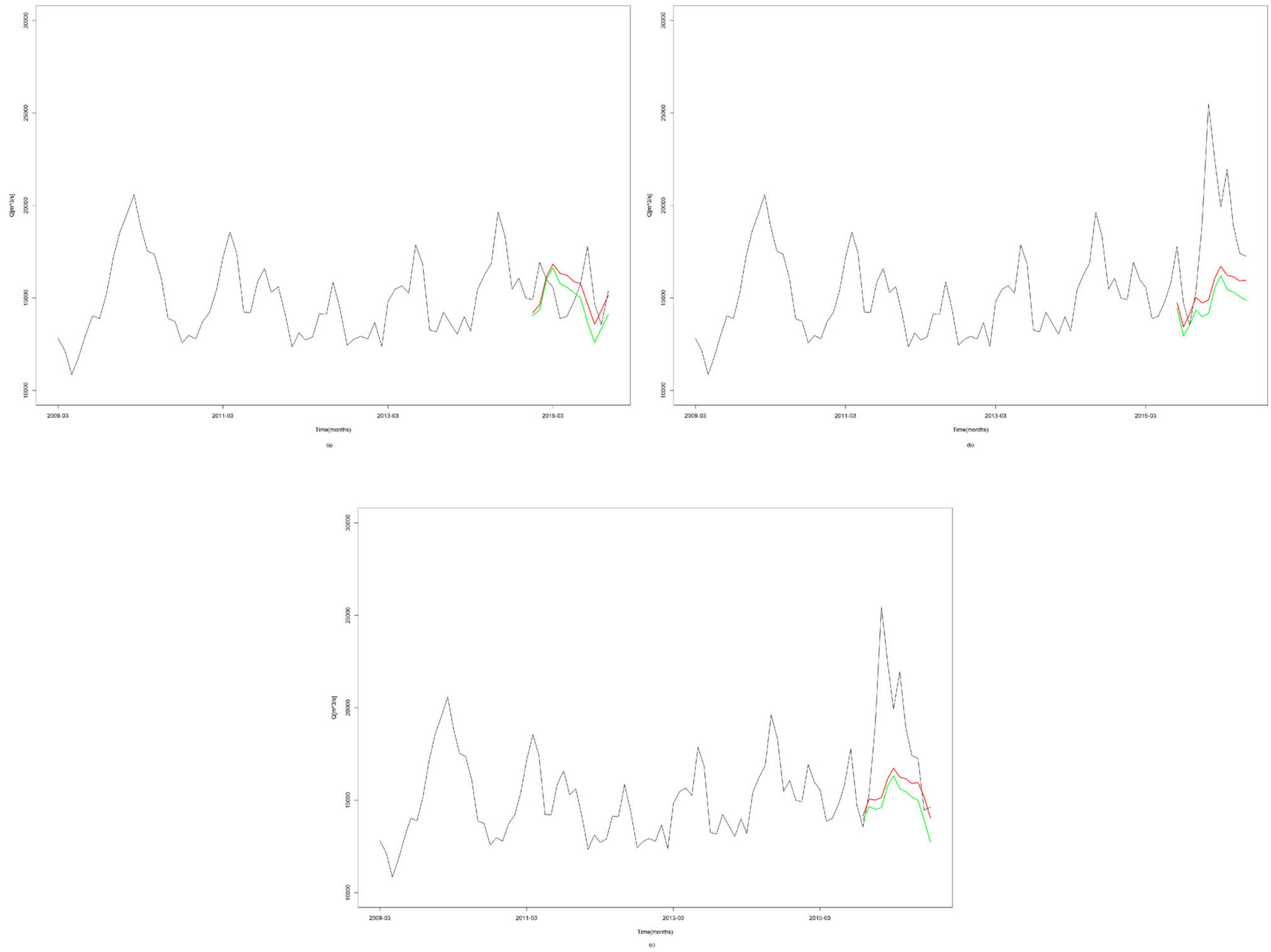


Figure 10. Examples of the 12-month forecast for monthly discharge in Túnel Subfluvial gauge station from October 2015 to September 2016. The red line represents the model that includes the exogenous variable, the green line represents the SARIMA without exogenous variable. (a) End tested January'16, (b) End tested July'16, (c) End tested May'16.

set coincided totally or partially with an El Niño event. We exhibit the errors for each model on each of these iterations in Tables 2 and 3. Moreover, to illustrate this, we exhibit the forecast for the last 6 and 12 months after a period where ENSO affected the study region in Figures 9 and 10.

In Table 2 and Figure 9, we can observe that when we are forecasting close to the extreme relative maximum that occurred at the beginning of 2016 the SARIMAX model performs much better. This makes sense, as the exogenous variable incorporated into the model was estimated from the NIÑO 3.4 index and the temporal period analyzed is influenced by an ENSO phenomenon.

In the 12-month forecast that is observed in Table 3 and Figure 10, we can also see that the SARIMAX model is performing better than the univariate model.

4. Conclusions

Interaction between different scientific communities turns out to be necessary and almost essential in order to be able to collaborate with decision makers in the hydrological, climatic and agriculture fields, among other areas.

The studies in the La Plata Basin are important for their hydrological implications for the southeast of South America (SESA). Several extreme events (floods and downspouts) have occurred in the recent past, which have provoked irreparable socio-economic damage in the different regions and communities that depend on the basin. In this sense, any climatic and hydrological study that might help prevent and mitigate these catastrophic effects in the LPB are essential for the well-being of society.

Hence, the monitoring of streamflow becomes indispensable, and statistical modelling is a useful approach for improving alert and control systems in the near future.

In this work, we applied statistical models to the problem described above. We considered using a time series model to forecast the monthly discharge in Túnel Subfluvial gauge station in the southern part of the La Plata Basin.

As it was seen in Meis and Llano (2018), SARIMA models could be useful to model the Paraná's streamflow; however, they lack the capacity to forecast its discharge under an extreme event scenery, such as an El Niño event. However, we chose the best model among 100 combinations of parameters for the SARIMA model. The selection we established considers the AIC criterion, as well as the NSE coefficient for both training periods. As it was expected, certain particularities were observed regarding estimated values, accordingly with Meis and Llano (2018).

To alleviate this, we repeated the exercise by adding to the model an exogenous variable describing the expected discharge obtained from the observed value of the NIÑO 3.4 index. Results showed that the exogenous variable did not improve the performance of the model on average; however, it was possible to observe that under situations in which the series presented extreme values, the new forecast was much better. This result is coherent with the work done in Meis et al. (2021), where we found that the relationship between the NIÑO 3.4 index and the discharge is stronger when the region is influenced by the phenomenon.

Even more, the joint distribution that was used to generate the exogenous variable works particularly well in the tail that corresponds to high values of the index and the discharge, suggesting that the signal that the expected discharge we built might not be too strong on average, but particularly accurate in extreme events. In this sense, by adding the exogenous variable we are getting a model that does not perform worse than the previous one on average, and it is stronger in certain temporal bounded windows related to extreme events of the El Niño phase.

Overall, these results show that it is possible to improve existing simple statistical models to perform well under extreme events that rely on an external natural forcing, such as ENSO. This is important for two reasons, these models have much lower computational cost and good interpretability, and extreme events are one of the most important situations in which decision makers must monitor discharge.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Data availability statement

Data used in this research are available through the web page at the Subsecretaría de Recursos Hídricos (Argentine Undersecretariat for Water Resources). The code used for the estimation of the discharge could be available under request. Libraries from R were applied.

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