

SEDIMENT TRANSPORT ESTIMATION FROM HYDROLOGICAL AND AUTOREGRESSIVE MODELS

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ABSTRACT

Hydrologic modeling allows the simulation of runoff and sediment processes, which are applied in integrated watershed management, soil and water nutrients, among others. However, these models require considerable amounts of input data. Sediment data is often lacking in quantity and quality, which leads to uncertainty in hydrological models. The objective of the present study was to propose a methodological alternative based on sediment time series in the Santa Cruz de Aquismón sub-basin, San Luis Potosí, Mexico, by means of autoregressive integrated moving average models (ARIMA) and the Soil and Water Assessment Tool (SWAT) model. The SWAT model was calibrated and validated with measured flows from the National Surface Water Data Bank (BANDAS) of station 26 241 (Ballesmi). Model calibration and validation performance was assessed with Nash-Sutcliffe Coefficient (NSE), percent bias (PBIAS), and the root mean squared error (RMSE). The SWAT model fit was rated as very good. The hydrologic model results were compared to the daily sediment estimates from three months in 1985 (June, September, and November) obtained from ARIMA models. The mean absolute percent error (MAPE) was 0.571, 0.168, and 0.029, respectively. The results indicated that the use of the ARIMA model for sediment estimation is useful when there are short time series with limited information, since it allows the completion of missing data series or short-term estimates.

Keywords: ArcSWAT, runoff, time series, ARIMA.

INTRODUCTION

Sediment assessment by modeling is used in studies to understand the structure, function, or problems in watershed management. It is also used to model runoff and erosion, as well as to estimate the influence of land use and climate change on the hydrologic balance. To improve sediment assessment, it is necessary to implement methodologies using approaches such as parameter optimization, operational management, and spatial distribution, among others (Song *et al.*, 2015). However, their application depends on the quantity and quality of available data, which must be

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free of missing values and consistent in magnitude. In case of having missing values, some methodologies cannot be applied, decreasing the analysis options. Regarding the magnitudes, the results obtained should be verified to ensure homogeneity in the data.

One of the most widely used models at the global level is the Soil and Water Assessment Tool (SWAT) model, which includes a hydrological module for sediment, nutrients, crop growth, and agricultural practices, and allows the analysis of ecosystem services (Shujiang *et al.*, 2020). One disadvantage of this model is the amount of complete input data required, which affects the quality of the results and makes runoff and sediment validation necessary.

In Mexico, most of the hydrometric stations provide incomplete daily data on runoff and sediment, which make it difficult to make decisions focused on watershed problems, erosion, and agriculture, among others, so methodologies are needed to correct the missing data. There is a great diversity of methods for estimating missing data on runoff, but few on sediment, which is often a limitation in the construction of a physical model such as SWAT. Therefore, the models mostly used in hydrology to estimate univariate time series are the ARIMA models, usually applied in the calculation of streamflow (Wong *et al.*, 2007).

Rivera-Toral *et al.* (2012) analyzed the performance of the SWAT model for estimating erosion in watersheds in Mexico and concluded that it is adequate, but emphasized the topographic factor (LS) with an independent calculation and a correction for slopes greater than 25 % without performing a sediment calibration due to lack of data. Salas-Martínez *et al.* (2014) and Sánchez-Galindo *et al.* (2017) used the SWAT hydrological model for biomass, runoff, and sediment prediction. This resulted in acceptable estimates, calibrated and validated with information from BANDAS, although they highlighted the reduced quantity and quality of the measurements. In recent years, Salas-Aguilar and Paz-Pellat (2018) generated a base with hydrological and physiographic data for sediment estimation in sub-basins in Mexico to address the problem that existing information presents a series of drawbacks regarding data uncertainty, gaps in the time series, and difficult access, so they synthesized the information of gauged basins so that any researcher could have access.

In this study, a methodology was proposed to estimate missing data in daily sediment time series using the historical record of the same station. The methodology was applied to the sediment transport of the Santa Cruz de Aquismón sub-basin, San Luis Potosí, Mexico. For this purpose, a model was built by means of SWAT, which considered the vegetation of 1985. After the calibration and validation of the model, the historical daily sediment data of the station were used to elaborate the ARIMAS for three months.

MATERIALS AND METHODS

Study area

This study was conducted in the Santa Cruz de Aquismón sub-basin, located in the municipalities of Aquismón, Ciudad Valles, Tanlaajás, and Tancanhuitz in the Huasteca

region of the state of San Luis Potosí, Mexico. The study area is located in the priority watershed defined by SEMARNAT as the confluence of the Huastecas, which covers an area of 27 650.50 km² and belongs to the hydrological region of the Pánuco River (Figure 1).

The Santa Cruz de Aquismón sub-basin was mapped using a Digital Elevation Model (DEM) downloaded from the Alos Parsar satellite, which has an area of 329.39 km² and is located within the Sierra Madre Oriental Physiographic Province, made up of folded Mesozoic sedimentary rocks where tectonic features and morphoclimatic changes have been determinant (Palacio-Aponte and Julio-Miranda, 2018). Most of the sub-basin area is located within the physiographic sub-province called Huasteco karst and corresponds to a tropical mountain range karst, and a smaller area corresponds to the Plains and Lomerios sub-province.

The predominant climate, according to the Köppen classification modified by García, is warm-humid A(f), with an average annual temperature higher than 18 °C, precipitation in the driest month is 40 mm, and average annual precipitation varies between 500 and 3000 mm (García, 2004).

INEGI's soil and vegetation charts indicate that the predominant soils are eutrophic vertisols and calcic leptosols, which are highly erodible. The natural vegetation in the sub-basin is in various stages of plant succession and is dominated by secondary

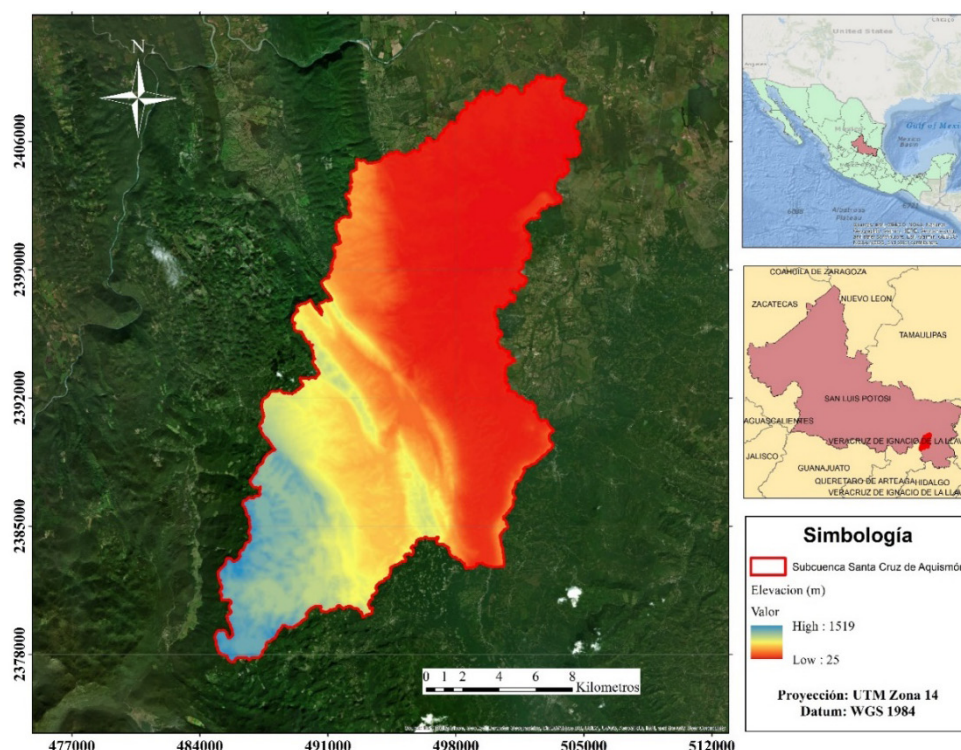


Figure 1. Location and elevation of the Santa Cruz de Aquismón sub-basin, San Luis Potosí, Mexico.

evergreen forest vegetation and secondary shrubby medium sub evergreen forest vegetation. In terms of land use, cultivated pastures predominate, followed by irrigated and rainfed agriculture. It is worth mentioning that the Huasteca region has experienced notable changes in land cover and land use, which have led to the alteration and reduction of the characteristic rainforest ecosystems (Reyes-Hernández *et al.*, 2006).

SWAT model application

Data base

The runoff and sediment model for the sub-basin was constructed from open access data. For daily precipitation, 11 meteorological stations obtained through the ERIC v 1.0 GIS platform were analyzed. Flow and sediment data were extracted from BANDAS, specifically from hydrometric station 26 241 at the outlet of the Ballesmi sub-basin (BANDAS, 2017). Finally, the natural vegetation in the sub-basin was obtained using a Landsat satellite image from 1985 with atmospheric correction corresponding to the dry period (February), to minimize the classification error due to the annual vegetation greenness present during the rainy season and low cloud cover.

ArcGIS 10.3 software with the ArcSWAT 2012 extension was used for runoff and sediment analysis. The simulation period was from March to December 1985 because this year has sufficient sediment and runoff data to evaluate this period; it is important to note that there is only sediment information from 1960 to 1997, and the months of January and February were discarded due to a lack of precipitation data. Since each climatological station analyzed contains daily data that influence a specific area of the sub-basin, Thiessen polygons were calculated to obtain the mean daily precipitation for the months of March to September for calibration and the rest for validation. The first 15 days of simulation were used as a model stabilization period and were excluded from the analysis. Runoff and sediment measurements in the sub-basin are limited by the amount of daily data available and the number of hydrometric stations. Therefore, calibration and validation were only performed with daily runoff data for the simulation period described above.

Runoff calibration and validation

The model was evaluated using the Nash-Sutcliffe efficiency coefficient (NSE), the percentage bias (PBIAS), and the root mean square error (RMSE). The NSE describes the deviation of the radius of the squared difference between the observed and simulated values and the variance of the observations. The value of this coefficient varies from $-\infty$ to 1, with $-\infty$ being a very low fit to the point of being considered unacceptable and unity a perfect fit (Equation 1). The PBIAS measures the average tendency of the simulated values to overestimate (positive sign) or underestimate (negative sign) the observed data, with 0 being the perfect fit value (Equation 2). The RMSE measures the average error magnitude, i.e., it is the representation of the data around a line with the

best possible fit, increasing with the variance of the error magnitudes (Equation 3) (da Silva *et al.*, 2015).

$$NSE = 1 - \frac{\sum_{i=1}^n (O_i - S_i)^2}{\sum_{i=1}^n (O_i - \bar{O})^2} \quad (1)$$

$$PBIAS = 1 - \frac{\sum_{i=1}^n (O_i - S_i) \times 100}{\sum_{i=1}^n (O_i)} \quad (2)$$

$$RMSE = \left[\frac{\left(\sum_{i=1}^n S_i - O_i \right)^2}{n} \right]^{0.5} \quad (3)$$

where: i is the position of the time series in pairs of measured and simulated data, n the number of even data, O_i the observed data at a given time position, S_i the simulated data at a given time position, and $\bar{O}$ is the mean of the observed data. [SRF1]

ARIMA models

There are several approaches to perform estimations that include moving averages and exponential smoothing, among which ARIMA stands out for its simplicity in understanding and application. ARIMA models are used to analyze stationary data series, based on the assumption that they follow a normal distribution and are limited by the linearity of the method. To improve this limitation, nonlinear stochastic models such as the ARIMA (p,d,q) have been proposed, where p corresponds to the autoregressive (AR), d is the differencing of the data, and q is the moving average (MA) (Box and Jenkins, 1976; Akhter *et al.*, 2019). One issue with the use of ARIMAS is the subjective order selection process. For this reason, Hyndman *et al.* (2020) include the Akaike Information Criterion (AIC) (Equation 4) in the Rstudio Forecast library to find these orders while taking into account the smallest possible data differentiation.

$$AIC = -2 \log(L) + 2(p + q + P + Q + k) \quad (4)$$

where: $k=1$ if $c \neq 0$ and 0 otherwise, L is the maximized likelihood of the model fitted to the differenced data; P and Q is the order for stationary processes (Aguado-Rodríguez *et al.*, 2016).

Sediment estimation with ARIMA

In this study, the daily sediment data obtained through modeling were used as a basis and compared to the ARIMAS calculated through the Rstudio program with the Forecast package (Hyndman *et al.*, 2020). Three 30-day data series were analyzed

for the year 1985 because this year has sufficient information for analysis and years after 1997 have a data deficit. The three series correspond to the beginning (June) and the end of the rainy season (September), and a cold dry season (November). The appropriate ARIMA function was calculated and plotted for each month. Once the ARIMA model was obtained, the estimation was performed for 10 days and the results were compared to the modeling data. Similar to the validation of the SWAT model, statistical criteria were used as proposed by Hyndman and Koehler (2006), and the RMSE and the mean absolute percentage error (MAPE) were calculated (Equation 5), since they are the most commonly used in time series.

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{(S_i - O_i)}{O_i} \right| \times 100 \quad (5)$$

RESULTS AND DISCUSSION

Calibration and validation of the SWAT model

Hydrological runoff models have different physical conditions depending on the region analyzed and the amount of data (for the validation and calibration processes), all of which generates uncertainty in basins that are not gauged or have a deficit of information. In this part of the work, the model calibration was performed for the period from March to May 1985 (Figure 2A) using modifications in the Curve Number (NC). These modifications were applied in a range of $\pm 7\%$ with a minimum value of -6.8% for the shrubby secondary vegetation of medium sub evergreen forest. The results obtained for calibration showed that the model is considered very good, since the NSE is 0.77, the PBIAS is 0.14, and the RMSE is less than half the standard deviation of 0.39. As for the validation, the analysis period from June to December 1985 (Figure 2B) showed that the model is also considered very good, with NSE values of 0.77, PBIAS of -2.85, and RMSE of 0.45. The very good values in the calibration and validation processes agree with SWAT runoff models in Mexico elaborated by authors such as Sánchez-Galindo *et al.* (2017) and Nevárez-Favela *et al.* (2021).

Sediments

As mentioned above, the lack of daily sediment data at the hydrometric station is a limitation since recording is made on a monthly and annual basis. This agrees with what was reported by Cruz-Arévalo *et al.* (2021), where the calibration of the SWAT model could not be performed due to the lack of sediment data in the Chapingo River basin, and concluded that this condition can generate unsatisfactory results that influence its reliability. In this model, the total annual sediment recording was used, since the monthly record for January and February showed sediment loads of 0 Mg, which implies that precipitation in these months was not intense or long-lasting enough to show considerable or measurable erosion in the sub-basin. Therefore, the

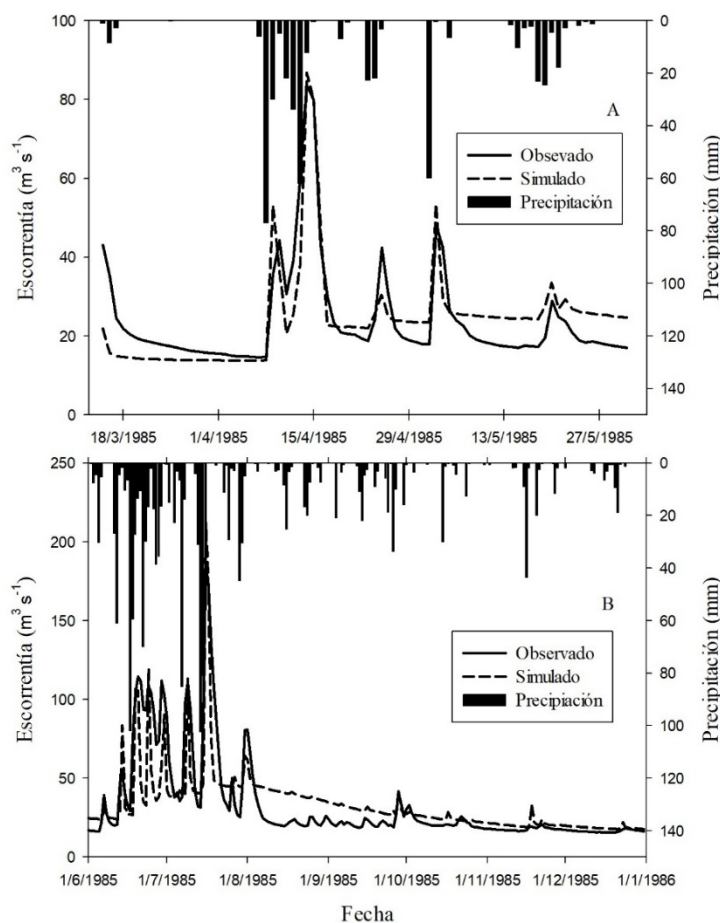


Figure 2. Comparison between observed and simulated runoff with the SWAT model in the Santa Cruz de Aquismón subwatershed, San Luis Potosí, Mexico. A: Calibration period (March-May). B: Validation period (June-December).

annual erosion observed, according to the BANDAS database, was 20 200 m³, which when affected by the relative density of the sediment, namely 1.1 Mg m⁻³ corresponding to clay soils (DOF, 2002), resulted in a measured sediment production of 22 220 Mg and that obtained with the model was 16 774. 94 Mg; that is, the model underestimates erosion by 5 445.06 Mg, which corresponds to 25.50 % of that observed.

Sediment estimation (ARIMA)

ARIMAS, in the field of hydrology and meteorology, has been applied in drought prediction, runoff coefficient determination, river flow harnessing (Thi-Thu-Hong and Nguyen, 2020), sediment concentration assessment (Rajaei and Jafari, 2020), and prediction of meteorological variables (Aguado-Rodríguez *et al.*, 2016), among others. This work focused on exploring the use of ARIMAS for sediment transport series in a

short period of time, a month, and opening up the possibility of completing historical time series or field measurements of a point of interest such as the same hydrometric station.

The first data estimation corresponding to the month of June was obtained from an ARIMA (5,1,0) with five autoregressives, one difference, and zero moving averages. An RMSE of 109.26 was obtained, which is greater than half the standard deviation, a PBIAS of -15.46, and a MAPE of 0.571, which indicated that the estimate is between good and unsatisfactory (Table 1, Figure 3A). This is due to the variability of the SWAT data, especially the last values, where there is an increase with respect to the first values, resulting in estimates with magnitudes different from those expected. This is consistent with Mora and Reyes (2013), who mention that the trend of the data defines the behavior of the ARIMA and the most intense fluctuations must be eliminated to regulate the results.

For the second series, the ARIMA (2,2,1) with two autoregressives, two differences, and a moving average corresponding to the month of September, RMSE values of 7.95 were obtained, which is greater than half the standard deviation, PBIAS of 16.02, and MAPE of 0.168, which indicated a better fit of the data, but still not a satisfactory

Table 1. SWAT, ARIMA values and 95 % confidence intervals (IC) in Mg ha⁻¹ for the months of June (Jun), September (Sep), and November (Nov).

DAY	1	2	3	4	5	6	7	8	9	10
SWAT Jun.	77.68	71.85	63.43	75.40	64.41	60.50	395.20	276.90	181.10	128.00
ARIMA Jun.	83.70	120.75	152.69	134.03	105.16	91.35	111.60	136.40	130.88	112.27
IC Low 95	-68.32	-88.48	-83.73	-117.47	-154.7	-206.7	-223.4	-222.9	-244.3	-273.1
IC High 95	235.72	329.56	389.12	385.53	365.09	389.41	446.57	495.73	506.02	497.6
SWAT Sep.	44.01	44.61	42.88	41.08	48.61	42.91	41.33	38.48	37.77	35.88
ARIMA Sep.	44.91	42.33	40.23	38.34	35.99	34.03	31.88	29.74	27.68	25.53
IC Low 95	37.02	28.09	18.68	7.51	-4.39	-17.07	-30.72	-44.99	-60.02	-75.72
IC High 95	52.81	56.57	61.79	69.17	76.37	85.13	94.47	104.48	115.38	126.78
SWAT Nov.	9.95	9.64	9.32	8.98	8.82	8.57	8.48	8.25	8.13	7.88
ARIMA Nov.	9.58	9.59	9.32	9.10	8.98	8.89	8.76	8.63	8.49	8.36
IC Low 95	-10.81	-15.81	-18.54	-21.38	-24.38	-27.96	-31.00	-33.90	-36.76	-39.59
IC High 95	29.98	34.98	37.19	39.59	42.64	45.74	48.39	51.16	53.74	56.31

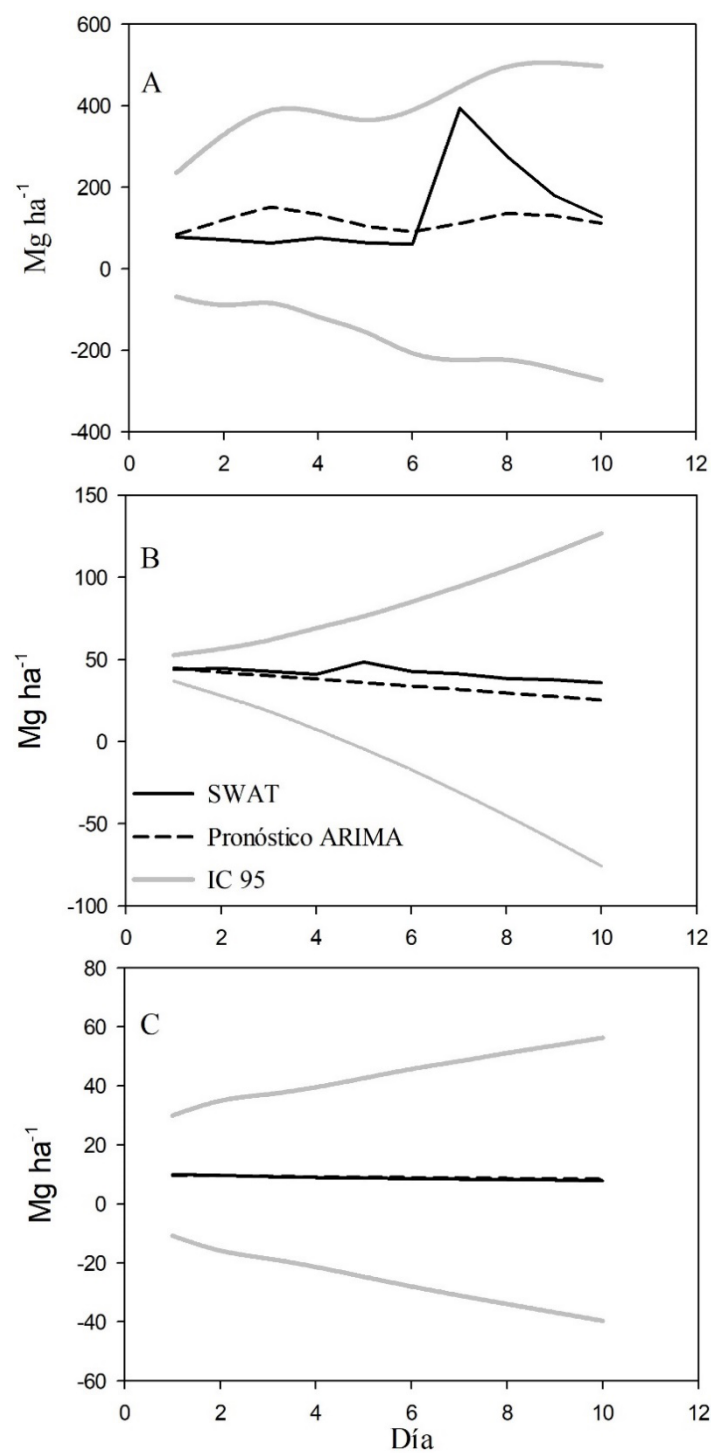


Figure 3. Comparison of SWAT values vs ARIMA forecast and 95 % confidence intervals (IC). A: ARIMA (5,1,0) of the first 10 days of June; B: ARIMA (2,2,1) of the first 10 days of September; C: ARIMA (2,2,3) of the first 10 days of November.

estimate for the RMSE. In this series, the estimates do not exceed the maximum and remain in a range with the SWAT values (Table 1, Figure 3B), which allows modeling possible maximum and minimum events, as suggested by Amaris *et al.* (2017), which allowed the calculation of annual runoff volumes.

Finally, the ARIMA (2,2,3) with two autoregressives, two differences, and three moving averages for the month of November, presented the best fit of the three months, with RMSE values of 0.293 which is less than half the standard deviation, PBIAS of -1.93, and MAPE of 0.029, and was satisfactory for each of the statistics. In this third series, the estimates result in values with a close approximation to those obtained with SWAT (Table 1, Figure 3C). As mentioned by Amaris *et al.* (2017), an adequate fit among the results is of utmost importance, since the estimates can be used to identify or forecast the variation of water resources and their behavior over short time periods.

The results show that the variability of the time series is the main limitation of the estimation; months with higher variability, such as June, are complicated to analyze. However, in seasons with lower variability and a clear trend, either positive or negative, the estimates can present minimal errors, as was the case in November. This agrees with the findings by Montari *et al.* (2000), who mentioned that in short periods of one month, the predicted data are satisfactorily approximate, but this was only tested with runoff.

CONCLUSIONS

The use of ARIMAS in the sediment domain is a fast and efficient way to make estimates to complete databases. However, the results depend on the time series that is analyzed to produce ARIMAS, which can underestimate and overestimate sediment for different periods of the estimate or can be very accurately adjusted.

In this study, the simulated sediment transport is close to the observed one, but the lack of databases, availability of information, daily data, and uncertainty in the correct records were an important limitation for the model, since the corresponding calibration for this parameter was not performed.

Finally, if there is a deficit in the available databases or if additional information is required in the short term, it is possible to make sediment forecasts with SWAT information using ARIMAS, but with time series of little variability and a trend; therefore, it is recommended for short time series and where a large amount of information is not needed, such as completing missing data series or short-term estimates.

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