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Precipitation pattern in Viçosa-MG: a case study via time series

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Abstract

This paper studies monthly precipitation time series in Viçosa MG, Brazil. We aimed to detect serial patterns in precipitation such as trend and seasonality and make predictions for the 2019 year. The idea was to understand water shortage events that occur in Viçosa as well as the water supply challenges for human consumption and agricultural production faced by urban and rural population. We used time series and SARIMA (1,0,0) x (0,1,1) model approaches selected based on Bayesian and Akaike Information criteria values (BIC and AIC, respectively). In addition, the ARCH (2) model, selected through AIC, was used to fit SARIMA (1,0,0) x (0,1,1) residues with heteroscedasticity. Our results reveal no changes in precipitation for Viçosa, MG, Brazil, with large variations observed only for specific periods.

Keywords: Rainfall; Environmental Preservation; Prediction; SARIMA; ARCH.

Introduction

Water is essential for living organisms, and so, hydrology studies are always booming among academic researchers and weather specialists. For Merten and Minella (2002), drinkable water is a finite natural resource, whose quality has been decreasing due to population growth and lack of water conservation policies. According to the World Health Organization (WHO), 785 million people have no access to treated water, and estimates are that by 2025 about half of the world's population will face water shortage. Each year, almost half a million people die on the planet due to water quality issues (WHO, 2019).

It is agreed that the lack of regular and uniform rainfall affects human activities. Besides water shortage for human consumption, large gaps between precipitation events impact crop production, an important source of income in Viçosa-MG and nearby areas. Fernandes *et al.* (2021) carried out a similar study, in which they verified the impact of drought in Southern Brazil, with a focus on water supply, crop production, and energy generation.

In terms of water supply for human consumption, the total precipitation index and the rainfall uniformity observed for Viçosa - MG are preoccupying, since the city has faced significant water shortage situations that led to the adoption of water rationing strategies. Sanches *et al.* (2017) already conducted a detailed study on the maximum and minimum precipitation patterns in Viçosa-MG, however, due to the importance of the subject, more information is needed regarding the impact that precipitation changes can inflict upon Viçosa and nearby towns.

It is also important to emphasize the impact of water shortage on research activities developed at Universidade Federal Viçosa (UFV). UFV features among the most prestigious universities in Brazil, especially in the field of Agricultural Sciences. Crop research trials developed at UFV require water for irrigation including during low-rainfall periods when the city also suffers from the lack of water.

After intense literature review, we identified only a limited number of studies involving precipitation patterns in Viçosa-MG, especially using time series. According to Morettin and Toloi (2006), time series studies are good tools to analyze precipitation events over the years since such data often contains serial dependence between observations, seasonality and, in some cases, trend components.

Soccol *et al.* (2010) studied precipitation in Lages-SC during the last 80 years, through gamma distribution, and identified the average precipitation pattern for the region. Santos and Aquino (2017) analyzed precipitation data from Castelo do Piauí, located in Northeastern Brazil, through descriptive statistics and Rainfall Anomaly Index, during 39 years (from 1963 to 2001), and found the predominance of dry and extremely dry years.

Mello *et al.* (2016) used a geo-statistical methodology to analyze precipitation patterns in Joinville, SC and observed that kriging and cokriging methods display good performance in identifying precipitation patterns. Costa *et al.* (2013) studied precipitation in the semi-arid region of Paraíba State, Brazil, across 100 years, and verified the influence of the Pacific Decadal Oscillation on its precipitation pattern.

Sanches *et al.* (2017) studied climate changes in Viçosa MG using maximum and minimum temperature, air relative humidity, and precipitation data through covariance analysis. Lemos *et al.* (2018) studied maximum and minimum temperatures, and also total precipitation in Lambari and Lavras, both municipalities located in the State of Minas Gerais, Brazil, through linear regression analysis.

The following studies used a methodology similar to the one we used here. Carvalho *et al.* (2016) analyzed climate data from the Ariquemes (RO) region, via SARIMA models to identify patterns for precipitation as well as other climate variables. Bleidorn *et al.* (2019) used the same SARIMA modeling approach to predict average flow rate of the Jucu River, located in the State of Espírito Santo. Lastly, Lopo *et al.* (2012) used the SARIMA methodology to model and predict the maximum ultra-violet radiation index in Natal, RN.

As shown, time series analysis for climate pattern studies may use a large number of methodologies, with ARIMA and SARIMA models being highly recommended to predict climate events based on previous occurrence of a series in study.

Besides its adequacy, a series allows researchers to make predictions that will serve as a decision-making foundation for experts in the area. Considering the dataset in study and the results observed in similar studies for other regions, we therefore chose a SARIMA modeling approach.

We describe here the precipitation behavior for Viçosa-MG, Brazil, in an attempt to detect modifications and trends over the time in study (from January 1968 to December 2018) using monthly precipitation data. Our main purpose was to study precipitation seasonality patterns and make rainfall predictions for the 12 months of 2019.

Material and methods

According to Morettin and Toloi (2006), a time series is formed by three non-observable components: trend, seasonality, and random noise. A more modern definition refers to a time series as the carrying out of a stochastic process, or yet, a set of observations or random variables ordered in time.

For trend analysis, the Augmented Dickey-Fuller's test (ADF) (DICKEY; FULLER 1979) requires the adjustment of the following regression model:

$$\Delta Z_t = \beta_1 + \beta_2 t + \pi Z_{t-1} + \sum_{i=1}^{m} \alpha_i \Delta Z_{t-i} + a_t \,, \qquad (1)$$

where $\Delta Z_t = Z_t - Z_{t-1} = Z_t - BZ_t$, are the series first difference values; ΔZ_{t-i} are the lagged values of the first difference series included in the model to eliminate autocorrelation of residuals so that the errors are white noise (uncorrelated observations, with mean zero and constant variance); m is defined by a minimization criterion such as the Akaike Information Criterion - AIC (AKAIKE, 1974); β_1 represents the intercept; β_2 is the deterministic trend coefficient; π is the unit root coefficient or stochastic trend coefficient and a_t are the white noise errors (homoscedastic and with mean zero).

Seasonality is a factor that occurs in a series at constant time intervals as long as its periodicity is equal to or less than one year, otherwise, it is called a cycle. Therefore, the presence of seasonality and its periodicity are verified through spectral analysis by decomposing the time series in the Fourier-frequency domain. Cryer and Chan (2008) define the intensities of Fourier frequencies as:

$$I(f_i) = \frac{2}{n}\left[\left(\sum_{t=1}^{n} Z_t \cos(2\pi f_i t)\right)^2 + \left(\sum_{t=1}^{n} Z_t \sin(2\pi f_i t)\right)^2\right], \quad (2)$$

In the graph of Equation (2), referred as Periodogram, Fourier frequencies f_i are represented on the x-axis and their respective intensities $I(f_i)$ are represented in the y-axis. In order to detect seasonal periodicity, we consider the frequency associated with the highest intensity to estimate the seasonal period using the formula $s = \frac{1}{f}$.

Following trend and seasonality analyses, the next step is to find a statistical model that best fits the data and also provides accurate future predictions. In this study, we adopted a Box and Jenkins modeling approach (BOX *et al.*, 2008) using SARIMA to model precipitation data and ARCH to model residual dependency of the time series.

The SARIMA model– seasonal autoregressive integrated moving averages is used to model time series with trend and seasonality components. Such model is described by Box *et al.* (2008) as:

$$\phi_p(B)\Phi_P(B)(1-B)^d(1-B^s)^D Z_t = \theta_q(B)\Theta_Q(B)a_t, \quad (3)$$

where $\phi_p(B)$ is the autoregressive polynomial of order *p*, $\Phi_P(B)$ is the seasonal autoregressive polynomial of order *P*, $\theta_q(B)$ is the polynomial of moving averages of order *q*, $\Theta_Q(B)$ is the polynomial of seasonal moving averages of order *Q* and a_t are the errors.

The ARCH model (Autoregressive Conditional Heteroscedasticity) was proposed by Eagle (1982) to estimate inflation fluctuations in the United Kingdom and its generalization. GARCH models (Generalized Autoregressive Conditional Heteroscedasticity) were proposed by Bollerslev (1986), as follows:

$$a_t = \sqrt{\left(\alpha_0 + \sum_{i=1}^{r} \alpha_i \alpha_{t-i}^2 + \sum_{j=1}^{s} \beta_j h_{t-j}\right)\varepsilon_t}, \quad (4)$$

where: α_i and β_j with *i*=1,2,…,*r* and *j*=1,2,…,*s* are the parameters to be estimated, ε_t is a random component with normal distribution, Student-*t* or GEV (Generalized Extreme Value).

The time series graph (FIGURE 1) was generated using monthly precipitation data from Viçosa-MG obtained in a conventional weather station located in the Department of Agricultural Engineering - UFV (UFV, 2019). Precipitation data was recorded on a daily basis from 1968 to 2018, in a total of 51 years or 612 monthly observations.

The Augmented Dickey and Fuller's test was used to detect the trend component, and the Periodogram to identify the presence of seasonality and its respective periodicity. Fisher's G test was used to determine statistical significance.

We used Akaike (AIC) and Bayesian (BIC) Information criteria to select the model (SCHWARZ, 1978). After ordering, we estimated the parameters using the Stats package in the R software (R, 2019) through conditional maximum likelihood.

The last step was verifying the selected models. The Ljung and Box's test (LJUNG; BOX, 1978) was applied to the data twice. First, Ljung and Box's test was applied to the residues to verify if the serial correlation had a good fit. Secondly, Ljung and Box's test was applied to the squared residues to verify if the model's residual variance was homogeneous.

Results and discussion

Precipitation data was obtained from a weather station located at Universidade Federal de Viçosa and consisted of monthly observations from January 1968 to December 2018. Figure 1 shows precipitation patterns in Viçosa-MG over the years.

Average precipitation during the time period studied was 106.5 mm per month with standard deviation of 108,92 mm. Highest precipitation amount was 626 mm of rain, recorded for December 2008. As expected, some months had no precipitation events. Absence of rain was observed in 31 months, the equivalent of 2 years and 7 months considering the studied period.

High standard deviation values are explained by the fact that some months display frequent and abundant rainfall, which corresponds to the wet season, usually from September to March, whereas April to August corresponds to the dry season, marked by low precipitation amount and occurrence. Such behavior can be observed in Figure 1, which contains the average monthly precipitation over the years.

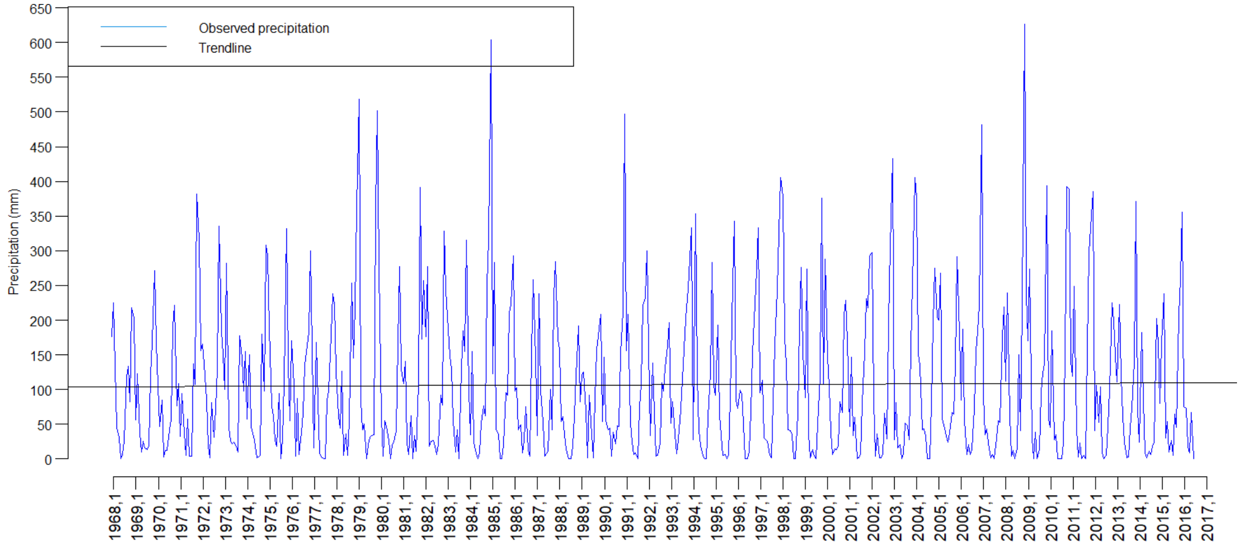
Figure 2 evidences the presence of seasonality with two distinct seasons (a dry and a wet season) when it comes to rainfall incidence. This result reinforces the need to model the seasonality component. We used a SARIMA modeling approach to deal with the seasonality component due to its adequacy.

After looking closely at the precipitation data over the years, we analyzed the data using statistical procedures that better represented the nature of our dataset.

Trend analysis with the respective test's p-values are shown on Table 1. The trend component was not significant, contradicting the common sense that precipitation nowadays in Viçosa is lower than it was before. This result agreed with that observed by Lemos *et al.* (2018) when studying precipitation events for the cities of Lambari and Lavras in South Minas Gerais.

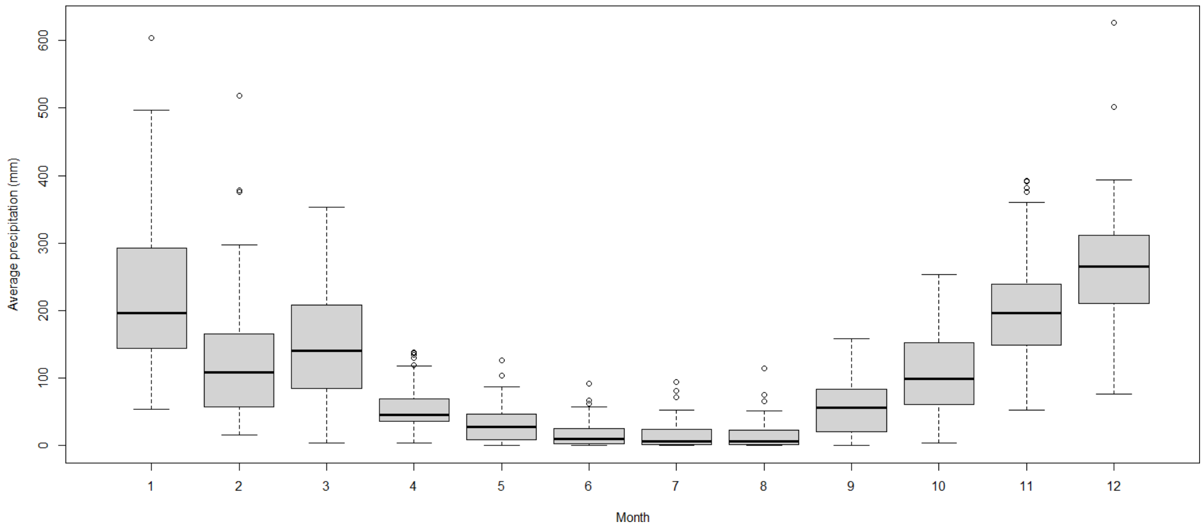
Results of the trendline analysis shown on Table 1, agreed with the visual assumption (Figure 1) that the time series studied here does not have any trend neither for increase nor for decrease in precipitation, demonstrating that water shortage problems are associated with

Figure 1: Precipitation time series for Viçosa-MG Série. Trendline appears in the middle part of the graph.



Source: authors.

Figure 2: Box-plot for the precipitation time series.



Source: authors.

Table 1: Trend analysis for the precipitation time series

Estimate	Standard deviation	*t*- statistics	*p*-value
Intercept −118.3561	641.2812	−0.1850	0.8540
Time (x) 0.1129	0.3219	0.3510	0.7260

Source: authors.

city growth and urbanization, and perhaps degradation of springs in rural areas.

Figure 2 contains the precipitation time series and its decomposition into three non-observable components: trend, seasonality, and random effect. By analyzing each component separately, we noticed that the time series apparently has no trend, which was confirmed by test results for the model's linear coefficient shown in Table 2. The presence of annual seasonality, on the other hand, was very clear when we analyzed this component separately.

Augmented Dickey-Fuller test (ADF) results are shown in Table 2. The hypothesis of unit root or stochastic trend (H_0: The time series has unit root or H_0: The time series has a stochastic trend) was rejected. The null hypothesis (H_0: The time series does not have a deterministic trend) was not rejected, suggesting that the time series has no deterministic trend. The ADF test was conducted using 22 lags for the first-difference variable. Such a number of lags was needed to remove residual autocorrelation.

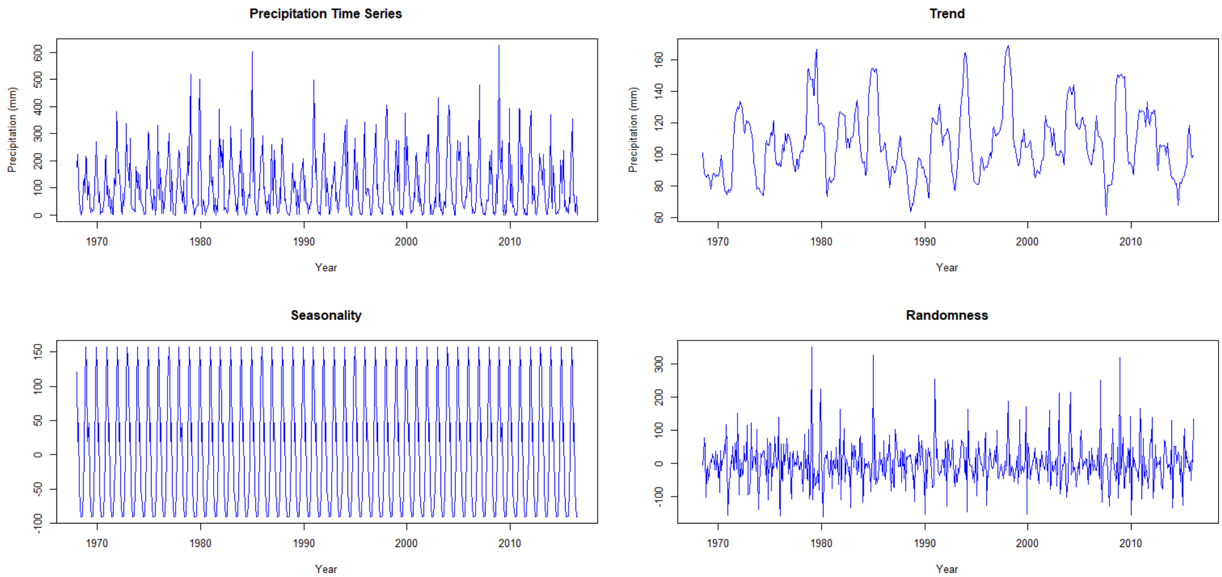
In the Periodogram analysis, the greater spectral intensity was associated with Fourier frequency of f=0,0841 indicating a periodicity of about 12 (estimated by the ratio s=1/f), in other words, precipitation data contains spatial

Table 2: Augmented Dickey-Fuller test results

Parameters	$\beta 1$	$\beta 2$	π
Estimates	127. 3279	0. 0071	−1. 2075
p-Value	< 0. 0001	0. 7257	< 0. 0001

Source: authors.

Figure 3: Time series decomposition.



Source: authors.

dependency from 12 to 12 observations. This result was already expected according to the visualization of our data.

In Table 3, we present model comparison results using AIC and BIC, in which the SARIMA (1,0,0) x (0,1,1) model was selected.

After defining, identifying, and estimating the model that best fitted our data, we tested the model's residue to verify adjustment quality. In Table 4 we present test results for the model's residues.

According to the Shapiro-Wilk test's results, the model's residues do not follow a normal distribution. As for the Ljung-Box test for residues, model's residues are not autocorrelated, and for the Ljung-Box test for squared residues the variances are not homogenous, requiring residue modeling.

We selected the SARIMA (1,0,0) x (0,1,1) model because it showed better adjustment compared to the others. Even though SARIMA (1,0,0) x (0,1,1) was selected as the best model, it was still inappropriate due to its residual variance heteroscedasticity. An alternative solution is to model the residues using non-linear ARCH/GARCH models to obtain homogenous variances without compromising modeling and prediction.

In Table 5, we present AIC estimates used for model selection. The GARCH(2,0)=ARCH(2)

Table 3: Model comparison

Model	BIC	AICc	MSE	MAPE
SARIMA(0, 0, 0) × (0, 1, 0)	6875.5100	6871.1690	1522.7160	40.6612
SARIMA(0, 0, 0) × (0, 1, 1)	6518.0060	6509.3330	780.4648	29.1273
SARIMA(0, 0, 0) × (0, 1, 2)	6523.9810	6510.9810	**763.0412**	28.8009
SARIMA(1, 0, 0) × (0, 1, 1)	**6516.6530**	**6503.6540**	806.5600	28.8372
SARIMA(2, 0, 0) × (0, 1, 1)	6522.4940	6505.1750	806.7800	29.0667
SARIMA(1, 0, 1) × (0, 1, 1)	6521.8490	6504.5300	803.7225	**27.9538**

Source: authors.

Table 4: Test results for residues of the selected model

Test	Statistics	p-Value
Shapiro-Wilk	0. 8931	< 0. 0001
Ljung-Box for residues	122. 8100	0. 9165
Ljung-Box for squared residues	45. 9330	< 0. 0001

Source: authors.

Table 5: ARCH/GARCH model selection

Model	AIC
GARCH(1,0)	6516.2430
GARCH(1,1)	6538.8650
GARCH(2,0)	**6506.3250**
GARCH(3,0)	6517.8230
GARCH(4,0)	6519.4400
GARCH(2,1)	6526.5730
GARCH(0,1)	6579.1170
GARCH(0,2)	6570.8180

Source: authors.

model showed the lowest AIC estimate and was therefore selected.

After modeling the precipitation data using the SARIMA (1,0,0) x (0,1,1) model to adjust for serial correlation and the ARCH (2) for variance of residues, the final result was a well-adjusted model with white noise residues, a requirement for this type of modeling.

In Table 6, we present monthly precipitation predictions for Viçosa 2019 based on the selected models. We also provide a column containing observed precipitation values for 2019.

The comparison between predicted and observed precipitation suggests accuracy in the model's predictability since all predicted precipitation values are within their respective confidence intervals and, in some months, such as February, May, October, and December, they were even closer to the observed values, all of them with less than 25% difference between predicted and observed values. All precipitation predictions, except those from April, October, and November, were higher than the actual precipitation. This happened probably because the overall annual precipitation mean (100.33 mm) was lower than the precipitation mean in 2019 (106.5 mm). The difference is 74.04 mm of rain compared to the other years.

The population of Viçosa-MG in 2020 is estimated at approximately 80 thousand inhabitants (IBGE, 2020), in 2010, it was approximately 72 thousand and in 2000, it was almost 60 thousand inhabitants (Maria et al. , 2014). This data shows a population growth of 33% in just 20 years, which, consequently, generates greater demand for water while the rate of precipitation remains constant.

As seen in the results, the precipitation index remains constant, thus combined with a growing population, the problem of lack of water should continue and even intensify if there is no intervention by the actors responsible for municipal water resources. In view of this, some measures need to be undertaken in order to preserve springs and the entire course of rivers, improve the conditions of the city's water reservoirs and adopt measures aimed at saving and re-utilising water resources already used by the community.

To preserve the quality and quantity of water in a given region, the rural population is essential. According to Garcia and Maia (2019), the maintenance of the agricultural producers in the rural area alone can serve as a barrier to urban expansion in densely occupied regions, a process that unprecedentedly increases the degree of degradation of ecosystems as well as

Table 6: Predicted and observed monthly precipitation (mm) in 2019.

Month	Predicted Precipitation	Observed Precipitation	Confidence Interval	
			IL	SL
Jan 19	248.26	29.8	77.64	347.06
Feb 19	262.31	155.8	0	261.44
Mar 19	245.80	130.8	17.95	289.25
Apr 19	121.21	115.4	0	19279
May 19	82.61	52.6	0	167.78
Jun 19	81.12	24	0	153.23
Jul 19	15.91	1	0	150.97
Aug 19	41.50	7.6	0	153.58
Sep 19	118.61	60.4	0	192.27
Oct 19	126.82	143.6	0	235.52
Nov 19	247.39	331.4	72.35	343.65
Dez 19	271.93	255.2	128.45	399.75

Source: authors.

the demand for natural resources. Furthermore rural producers can be induced and encouraged, including financially, to use their land consciously, preserving the springs.

Thus, it is necessary to take care of degraded rural areas. According to Garcia and Maia (2019), the recovery and maintenance of forest areas are fundamental actions to guarantee or expand the flow of ecosystem services in watersheds, conserving the water in the soil of a given region for a longer time.

In addition to preserving the springs and conserving the water that will benefit the entire population, rural producers can also improve the quantity and quality of water on their property, aiming at greater production. According to Christofidis (2013), globally, the productivity obtained by the practice of irrigated agriculture is 2.7 times greater than that obtained by traditional agriculture. Furthermore, the United Nations Food and Agriculture Organization (FAO) estimated an 11% increase in water demand for irrigated agriculture in the period between 2008 and 2050 worldwide, due to the increase in population and greater demand for food (FAO, 2011).

Conclusion

This study aimed to propose a methodology for evaluating and monitoring rainfall in the city of Viçosa-MG, through time series modeling via the SARIMA model. The research allowed a detailed analysis of the behavior of this important statistical series and indicated its main characteristics. The model also allowed for the presentation of forecasts with very reasonable accuracy for a 12-month window.

The study concluded that the time series of total monthly rainfall in the city of Viçosa-MG remains unchanged since the beginning of data recording in January 1968.

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