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Pluviometric forecast in Campina Grande via modeling Box-Jenkins

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Abstract
Precipitation is a variable that has been constantly studied over time to describe the characteristics of the rainfall regime in a given region. The precipitation values in northeastern Brazil have high variability presenting a high volatile behavior with long dry periods and short periods of high rainfall precipitation. For this reason, this hydrologic variable has been a crucial object of study in Climatology and Hydrology. Thus, rainfall studies in this region have been constantly developed to investigate its behavior over the years. The SARIMA model class has good behavior when used for modeling meteorological data. The present study aimed to analyze the behavior of a series of precipitation in the city of Campina Grande, Paraíba, using the class of models developed by Box and Jenkins to investigate the behavior of precipitation values in this locality and evaluate the predictions. The model that best described the behavior of the variable was $SARIMA(3,0,1)x(2,1,1)_{12}$modeling the precipitation data with high variability.
Keywords: Precipitation, Campina Grande, SARIMA

Previsão pluviométrica em Campina Grande via modelagem Box-Jenkins

RESUMO
A precipitação é uma variável que vem sendo constantemente estudada ao longo do tempo para descrever as características do regime pluviométrico de uma determinada região. Os valores de precipitação no nordeste do Brasil possuem alta variabilidade apresentando um comportamento altamente volátil com longos períodos de seca e curtos períodos de alta precipitação pluviométrica. Por esta razão, esta variável hidrológica tem sido um objeto de estudo crucial em Climatologia e Hidrologia. Assim, estudos de precipitação nessa região têm sido constantemente desenvolvidos para investigar seu comportamento ao longo dos anos. A classe de modelo SARIMA tem bom comportamento quando usada para modelar dados meteorológicos. O presente estudo teve como objetivo analisar o comportamento de uma série de precipitações na cidade de Campina Grande, Paraíba, utilizando a classe de modelos desenvolvida por Box e Jenkins para investigar o comportamento dos valores de precipitação nesta localidade e avaliar as previsões. O modelo que melhor descreveu o comportamento da variável foi 〖SARIMA(3,0,1)x(2,1,1)〗_12 modelando os dados de precipitação com alta variabilidade.
Palavras-chave: Precipitação, Campina Grande, SARIMARESUMO

1. Introduction

In hydrology, precipitation is defined as all water coming from the atmospheric environment that reaches the earth's surface, so fog, rain, hail, hail, dew, frost, and snow are different forms of precipitation. The difference between these precipitations is due to the water's state (BertonI & Tucci, 1993). Rainfall is a relevant variable for climate studies, so understanding their behavior is crucially important.

Among the meteorological phenomena of economic importance for society, precipitation can be highlighted since this variable is related to water scarcity, flooding, crops, and, consequently, the feeding and survival of animals and people (Costa et al., 2015). Thus, the assessment of climate forecasting can be considered an essential tool for controlling water supply in cities in the improvement of the electricity and agricultural sector. This fact corroborates improving the quality of socioeconomic activities (Minuzzi, 2017). According to Marengo (2010), the Northeast region is naturally characterized as having a high potential for water evaporation due to the vast availability of solar energy and high temperatures with great climatic variety. Most of the region has a semi-arid climate, characterized by low rainfall and high evaporation, with areas reaching cumulative rainfall of 500 mm per year, similar to the desert regions (Marengo and Silva Dias, 2007).

Historically, the Northeast has been affected by significant periods of drought and flood, with reports that since the early seventeenth century, with long periods of drought even in rainy seasons. The presence and permanence of these rainfall irregularities make it difficult to plan the agricultural and water resources in the region. Such conditions caused the evasion of the northeastern population in search of sustenance and better survival conditions. According to Galvíncio et al. (2017), the climate of different regions may fluctuate correspondingly to natural variations observed through environmental studies and the so-called Climate Variability. These studies have become more relevant every day and can be commonly approached with spatiotemporal analyzes.

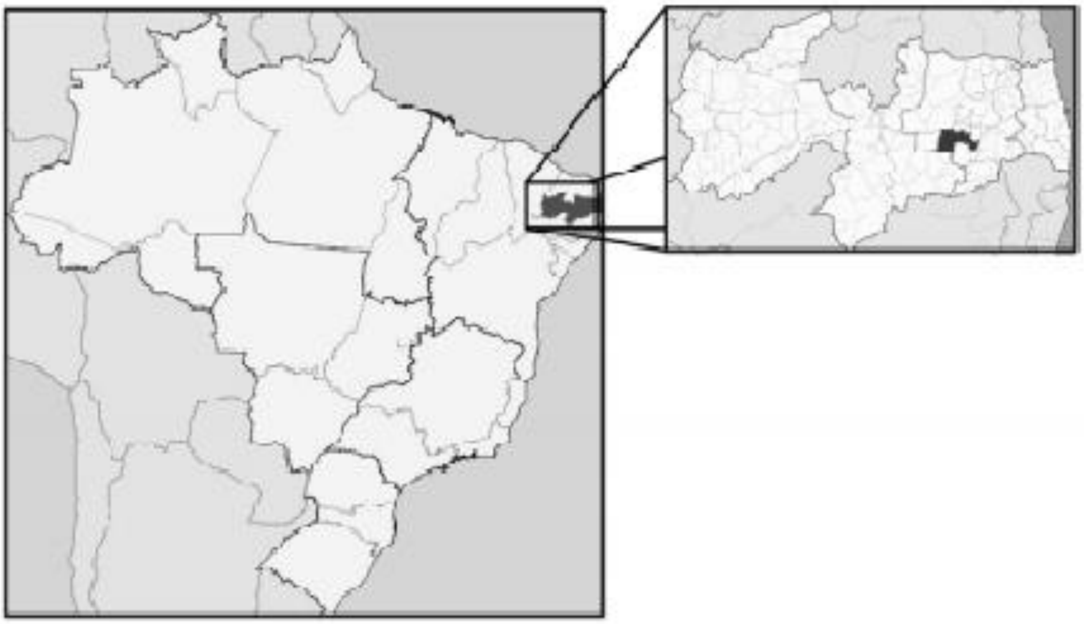
The city of Campina Grande, Paraíba, has high variability rainfall indexes. The locality has experienced a prolonged drought due to the low frequency of rainfall and, consequently, decreased the capacity of the Boqueirão dam, a reservoir that supplies Campina Grande and other cities in the region. To the detriment of this drought period, the municipalities supplied by the spring suffered severe rationing. Henrique and Dantas (2007) mention that in the Paraiba region, where the city of Campina Grande is located, evapotranspiration plays a significant role because of the water deficits throughout the year, constituting limitations on agricultural production and a permanent source of risk almost all over the region, primarily in dry areas with climatic characteristics close to semi-arid.

Several methodologies have been proposed in the literature to study the occurrence of events over time and make predictions; among them, we can highlight the Box and Jenkins (2015) methodology, which proposes a class of models to analyze these events, including the presence of seasonality and trend in the series. (Lucio et al., 2010) verified that all approaches imputed to the series of interests (Exponential Smoothing and Box-Jenkins Model) revealed that precipitation estimates are acceptable within the meteorological scope. In fact, for both models, individual, as in the combined model, the results of the forecasts are suitable, allowing the researchers to deduce the behavior of quarterly precipitation series. The series tend to converge towards stability concerning the component seasonal.

In this work, we analyzed a series of total monthly accumulated precipitation from January 1994 to May 2018 from a station located in Campina Grande, Paraíba, to verify the behavior of the series via trend and seasonality components, as well as forecasting precipitation values with models proposed by Box and Jenkins.

2. Materials and methods

Figure 1 shows the location of Paraíba state on the map of Brazil (Fig. 1 a)), with emphasis on the municipality of Campina Grande and its urban network (Fig. 1 b)). The meteorological data obtained for this work were made available by the National Institute of Meteorology (Inmet). The series consists of 293 observations, from January 1, 1994, to May 31, 2018, forming a monthly series of approximately 24 years. Analyzes were performed using the R program (R Core Team, 2018).



a)

b)

Figure 1 - a) Location of the state of Paraíba in the map of Brazil with emphasis on the state of Paraíba, where the municipality of Campina Grande is located (Source: INMET), and b) urban network of the city of Campina Grande in 2019 (Source: Secretariat Grande Traffic and Public Transportation - STTP).

Time series models can be seen in the most diverse areas of study (Tablada et al., 2016): health (Bicalho et al., 2014), meteorology (Liska et al., 2013), economics, biofuels (XavieR et al., 2018), among others. The most widespread time series model class is the approach proposed by Box and Jenkins (Box; Jenkins, 2015), which breaks down the time series into autoregressive moving average components (Sharma et al., 2009), with a focus on behavior analysis, trends, and correlations of observed data (Oliveira et al., 2015) and, from this analysis, obtain viable and reliable estimates for the phenomenon under study. The Dickey-Fuller (Dickey and Fuller, 1981) and Phillips-Perron (Philipps and Perron, 1988) unit root tests were used to verify stationarity and the Mann-Kendall test (Mann, 1945; KendalL, 1975) to evaluate the existence of a trend.

Seasonal Autoregressive Integrated Moving Average time series model

The data set repeats events over time in many situations, denoting seasonality. One way to handle such situations is to use a seasonal periodicity difference for the series that is defined as follows:

$$\nabla_s Y_t = Y_t - Y_{t-s} \qquad (2.2.1)$$

Thence, for monthly time series, changes are considered from January to January, February to February, etc. Note that for a series of size n, the seasonal difference series will be of size n-s. Below is an appropriate case for the use of seasonal differentiation.

$$Y_t = S_t + e_t$$

with

$$S_t = S_{t-s} + \varepsilon_t 1$$

Where e_t and ε_t are the white noise of the series, S_t is a “random walk”, respectively. Therefore, applying the seasonal difference as in Equation (2.2.1).

Considering some mathematical artifices, it is possible to show that the series is stationary and has an autocorrelation function of a moving average process MA $(1)_s$.

A Y_t process is said to be a multiplicative seasonal ARIMA model with regular non-seasonality if the differentiated series satisfies an ARMA $(p,q)X(P,Q)_s$ model with seasonal period s

$$W_t = \nabla^d \nabla_s^D Y_t \qquad (2.2.2)$$

The hypothesis for analysis proposed by Box and Jenkins (BOX; JENKINS, 2015) is based on the construction of functions defined in an iterative cycle using their time series data to find an adequate mathematical prediction structure. In the context of time series, a significant definition that should be considered during the series analysis is the condition of stationarity which is an assumption that must be observed to work with the series. Among the models that can be adjusted in a stationary series highlighting the moving average model (MA), the autoregressive model (AR), and the autoregressive moving average model (ARMA). For the series that do not have the stationarity characteristic, one must make one or more differences in the data to obtain the stationarity. Thus, models for non-stationary series, such as IMA, ARI, and ARIMA, are applied.

It is said that Y_t is an ARIMA $(p,d,q)X(P,D,Q)_s$ model with seasonal period s. Using the Backshift operator, the model can be rewritten as follows

$$\phi(B)\Phi(B)\nabla^d \nabla_s^D Y_t = \theta(B)\Theta(B)e_t$$

Parameters Estimation and Information Criteria

In time series analysis, several methods can be used for parameter estimation. The maximum likelihood method was utilized to provide better estimates with errors than the other methods, such as the least squares and moments method. The selection of the best model was performed using the Akaike information criterion - AIC (AKAIKE, 1998), the Bayesian information criterion - BIC (AKAIKE, 1978), and the root mean square error (RMSE).

Model Validation

To verify the assumptions, some statistical tests in the literature were used. For the normality of the residues, the Shapiro-Wilk test (Shapiro and Wilk 1965) was used to certify the randomness of the Runs test (WALD and WOLFOWITZ 1943) and to verify the independence of the residues the Ljung-Box test (LJung and Box), 1978). All of these tests are widely used in the literature, especially in climate science studies, for instance, the texts of Stagge et. Al. (2016), Camel et.

Al. (2018), Murat, et. Al. (2018), Nisar, et. Al. (2019), among others.

3. Results and discussion

A descriptive analysis was performed to investigate the precipitation values from January 1, 1994, to April 30, 2018, calculating the quantities per month, the results are described in Table 1. On average, May, June, and July were the wettest months in the study, such months belong to the rainy season in the northeastern region (MOLION, 2002). It is verified that for all months the values of the asymmetry coefficient (CS>0) indicate positive data asymmetry. It is noticed that, in general, there were months with zero precipitation. The maximum total precipitation value in the series was 361.1 mm. It is also observed the coefficient of variation of the precipitation series is above 20%.

To facilitate the visualization of the behavior of the series and investigation of the seasonality a Monthplot was performed, which consists of calculating the monthly averages and leaving them indicated on the graph using a horizontal line. Figure 2 exhibits the average cumulative rainfall (in blue) indicating an increase in the first six months and the opposite in the following ones

Table 1: Descriptive statistics for precipitation values (in millimeters) in Campina Grande, Paraiba, Brazil.

Months	N	Mean	Median	Minimum	Maximum	S	Cs	C_k	Cv%
January	25	47,076	27,200	1,000	279,000	58,022	2,562	7,455	123,25
February	25	63,404	30,100	2,700	244,600	69,212	1,406	1,054	109,16
March	25	88,340	88,800	14,400	247,100	56,244	1,038	0,770	63,66
April	25	91,428	91,600	5,000	183,200	56,847	0,045	-1,324	62,18
May	24	103,117	88,850	13,300	361,100	74,357	1,637	3,450	72,11
June	24	135,446	125,450	25,800	263,300	67,427	0,198	-0,884	49,78
July	24	118,721	110,550	18,500	333,900	68,031	1,139	1,781	57,30
August	24	68,500	57,350	8,800	200,700	44,815	1,028	0,896	65,42
September	24	33,775	18,950	2,300	149,400	36,990	1,577	1,863	109,52
October	24	13,942	9,800	0,400	51,500	12,410	1,224	1,113	89,01
November	24	11,908	6,150	0,000	68,500	16,765	1,948	3,260	150,79
December	24	17,108	10,800	0,000	60,000	17,298	1,095	-0,045	101,11
Total	427	66,083	44,700	0,000	361,100	64,515	1,312	1,724	97,63

n: number of observations; S: standard deviation; Cv: coefficient of variation; Cs: coefficient of asymmetry; Ck: kurtosis coefficient.

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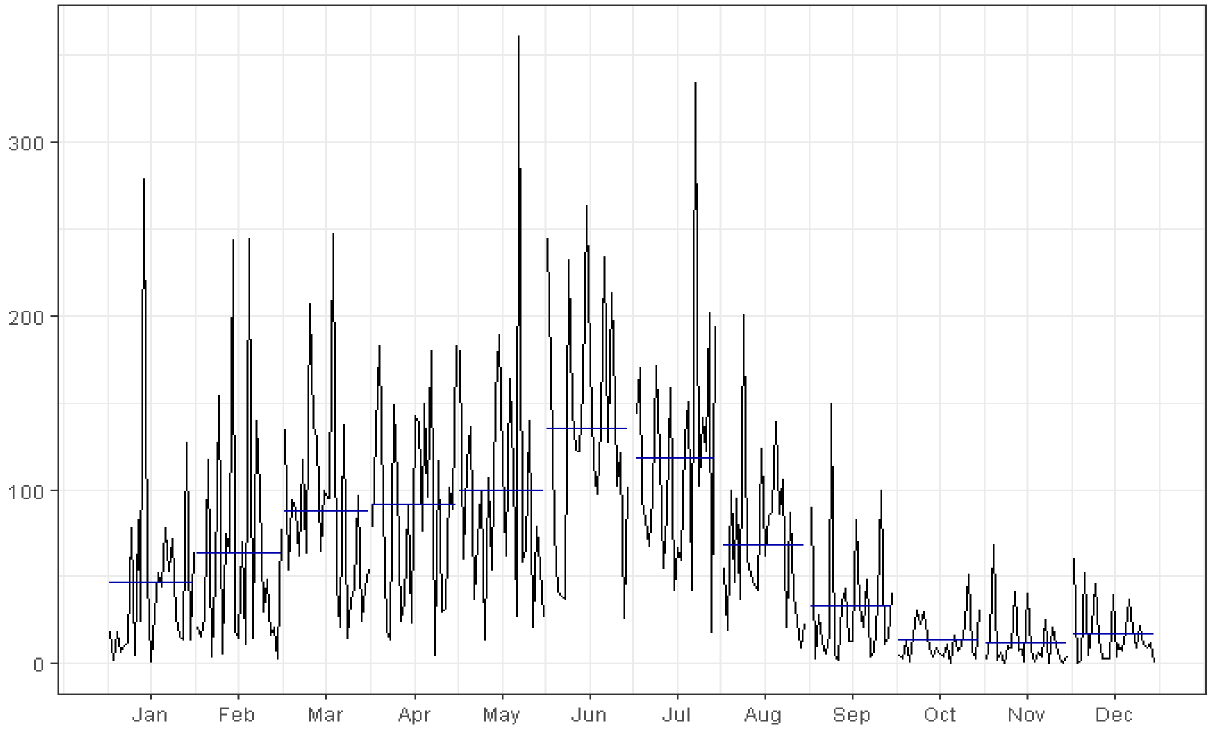

Figure 2: Monthplot of accumulated precipitation.

Figure 3 presents the decomposition of the series containing the monthly accumulated precipitation data with the trend, seasonality components, and residuals. It is observed that it is possible to perceive the presence of a slight trend component. The seasonality component is easily identifiable through the behavior presented in the observed values with a well-defined period. Last but not least, there is the random component, which is the filtered component of the other effects series, suggesting there is a random behavior. Costa (2019) conducted a study in Cruz das Almas, Bahia, discussed the importance of decomposing the rainfall series for a better understanding of the components of the series.

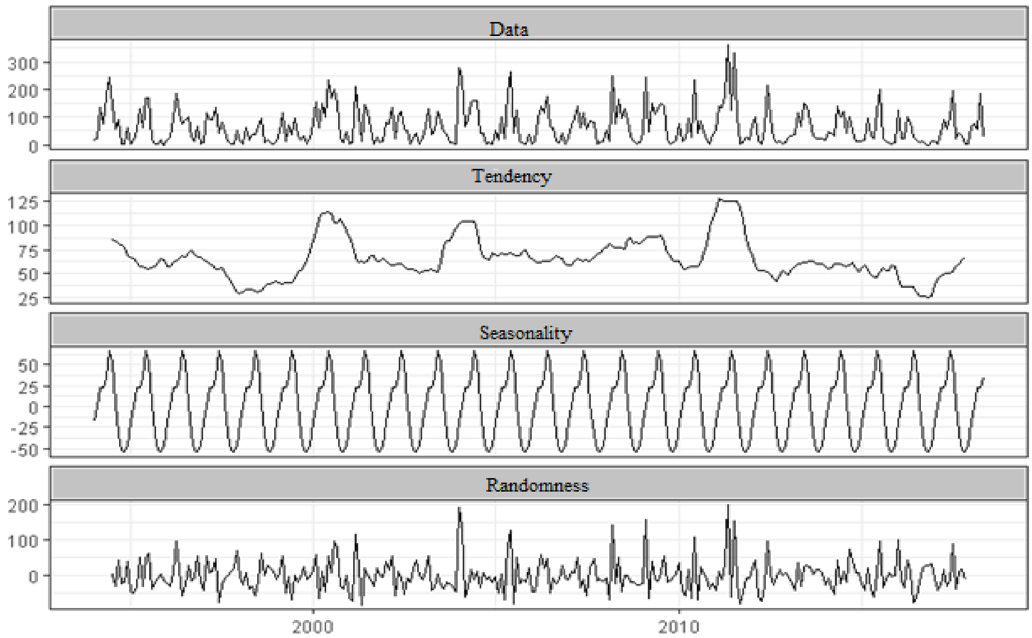

Figure 3: Additive decomposition of the precipitation series.

Figure 4 displays the ACF and PACF graphs of the precipitation series. The ACF describes how a present value of the series is related to past values. ACF considers time series components when finding correlations, so it is a complete autocorrelation function in which it provides autocorrelation values of a series with their lagged values. it's noticeable that the behavior of the ACF indicates a model with seasonality. These values are plotted over a confidence band in the form of a complete autocorrelation plot. PACF is the partial autocorrelation function, and it is widely used to identify the number of parameters of a model under study. Unlike ACF, it finds residual correlations with the later lag value by classifying them as "partial" or "not complete". The PACF graph indicates a model with few parameters.

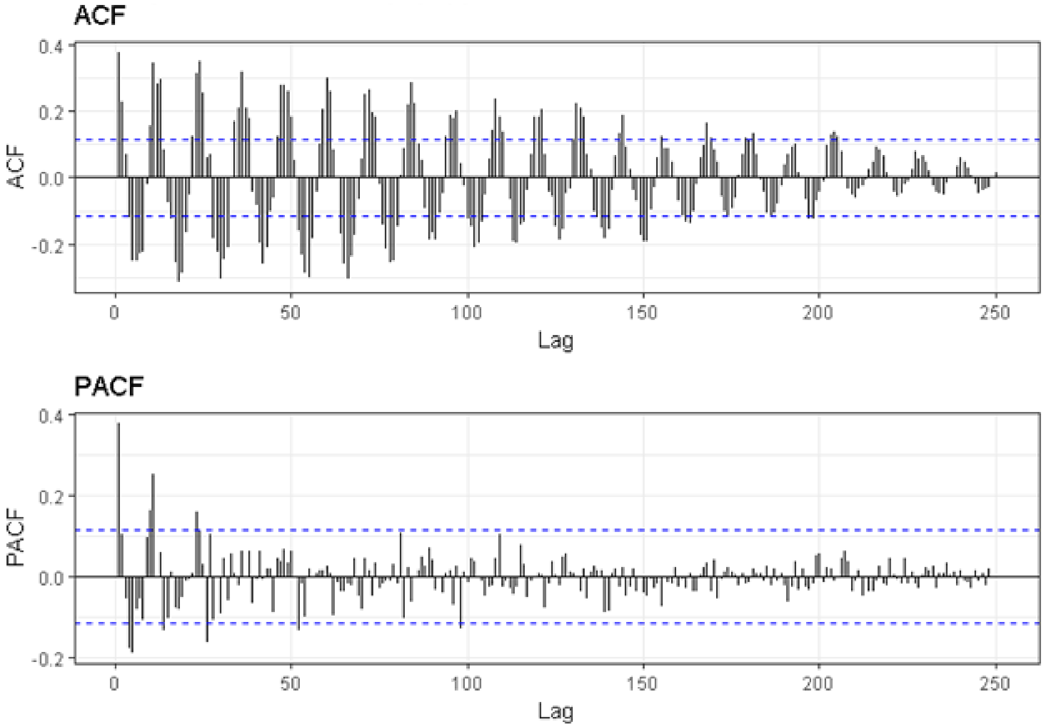

Figure 4: Plots of autocorrelation (ACF) and partial autocorrelation (PACF) functions, respectively.

To confirm the presence of stationarity in the precipitation series, we performed Dickey-Fuller and Philips-Perron tests. Table 2 exhibits the results, and it is possible to verify from both unit root tests that the accumulated precipitation series in the municipality of Campina Grande is stationary, that is, the values of the series are concentrated around the mean with approximately constant variability.

Table 2: Unit root tests for stationary monthly cumulative precipitation series.

Test	**Statistics**	**P-value**
Dickey-Fuller	-11,251	< 0,01
Phillips-Perron	-181,54	< 0,01

Figure 5 shows the seasonality in the precipitation series. One can see that the first months of the year show the highest peaks of accumulated precipitation (in red). In blue the months with very little accumulated precipitation, giving indications of seasonality. Some previous studies have identified seasonality in precipitation in the northeast region of Brazil: Rao et. al. (2015) analyzed the trend and seasonality of rainfall in all regions of Brazil from 1979 to 2011, the study detected an increase in precipitation in the western part of the Brazilian Northeast, as well as the study developed by Santos and Brito (2007), which identified trends in increasing annual total precipitation for the states of Rio Grande do Norte and Paraíba with the methodology adopted by Haylock et al. (2006). Gastmans et. al. (2017) detected seasonality effects on precipitation throughout the eastern Brazilian region studying the control of spatial and seasonal variations in the isotopic composition of precipitation. Hounsou-Gbo et. al. (2016) combined prior knowledge of precipitation seasonality in much of Northeastern of Brazil with ocean conditions in the equatorial Atlantic to predict rainfall dynamics based on dry and rainy periods over the years.

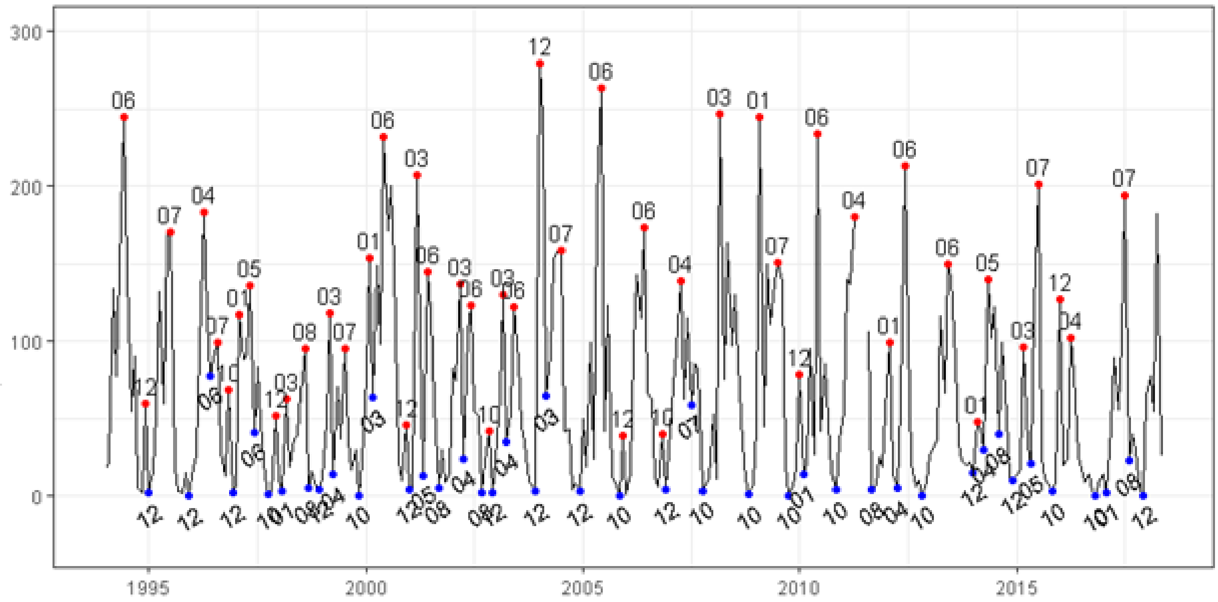

Figure 5: Monthly cumulative precipitation with highlighted months (blue and red emphasizing seasonality).

Table 3 displays the AICc, BIC, and RMSE values for the best models evaluated using the auto.arima function of the forecast package (R Core Team, 2018). In this way, based on the comparison criteria, the model chosen for the accumulated precipitation was ARIMA (3,0,1) x (2,1,1)12.

Table 3: Values of AICc, BIC, and RMSE for the models considered.

Models	AICc	BIC	RMSE
Model 1: ARIMA(3,0,0)x(2,1,0)$_{12}$	895,91	917,44	1,12
Model 2: ARIMA(3,0,1)x(2,1,1)$_{12}$	**857,92**	**886,50**	**0,98**
Model 3: ARIMA(1,0,0)x(2,1,0)$_{12}$	901,15	922,67	1,13

To verify if the chosen model is well adjusted and if the residual component can be considered white noise, the Shapiro-Wilk, Ljung-Box, and Runs statistics tests were performed, indicating normality, fit quality, and randomness, respectively (Table 4). The results suggest that the null hypothesis was not violated, visually verified in Figure 6.

Table 4: Tests of normality, independence, and randomness of the residues.

Tests	Statistitics	P-value
Shapiro-Wilk	0,99	0,30
Ljung-Box	15,64	0,73
Wald-Wolfowitz (RUNS)	148,00	1,00

We observe that the residues do not present a tendency; through the ACF it is verified that there are no significant autocorrelations, and the graph of the p-values of the Ljung-Box test indicates that the residues do not have dependence (Figure 5). Pereira et al. (2015) modeled the behavior of the annual rainfall averages in Areia, Paraiba, and used Box-Jenkins modeling via the SARIMA model. The authors concluded that the model fit was satisfactory, obtaining similar results regarding the residual behaviors of the SARIMA model.

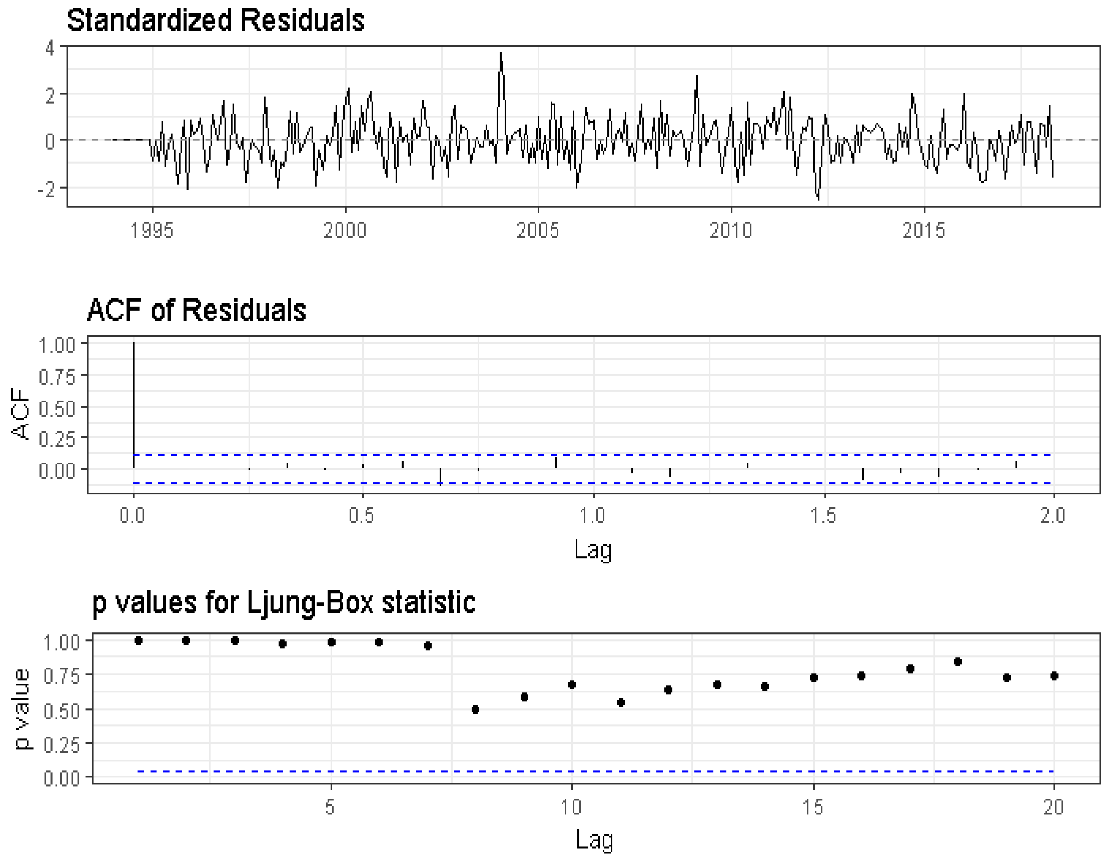

Figure 6: Graph of standardized residues, ACF of residues and Ljung-Box test for the ARIMA model (3,0,1) x (2,1,1)12

A forecast for monthly precipitation between February and December 2018 was obtained based on the estimated SARIMA model for the phenomenon. Figure 7 illustrates the forecasted values with forecast ranges with 95% and 80% confidence margins along with the observed values used in the analysis. The highest precipitation rates were estimated for the months of May, June, and July 2018, with an average maximum rainfall of 44 mm. The 95% confidence interval indicates that this value can range from 8.71 to 79 mm of rain approximately. The lowest rates were forecast for October, November, and December 2018, with a minimum of approximately 3.9 millimeters of rainfall during October 2018. Considering the 95% confidence interval, this estimate can range from approximately 0 to 39 millimeters of rainfall. In general, models of the ARIMA class tend to predict mean values based on observations. Long-Range predictions must be carefully evaluated, especially in natural phenomena (such as precipitation, for example), where there are many external factors involved. However, by using the seasonal component in the ARIMA model it was possible to predict a dry and rainy season for 2018, indicating that the model was sensitive to seasonal variations.

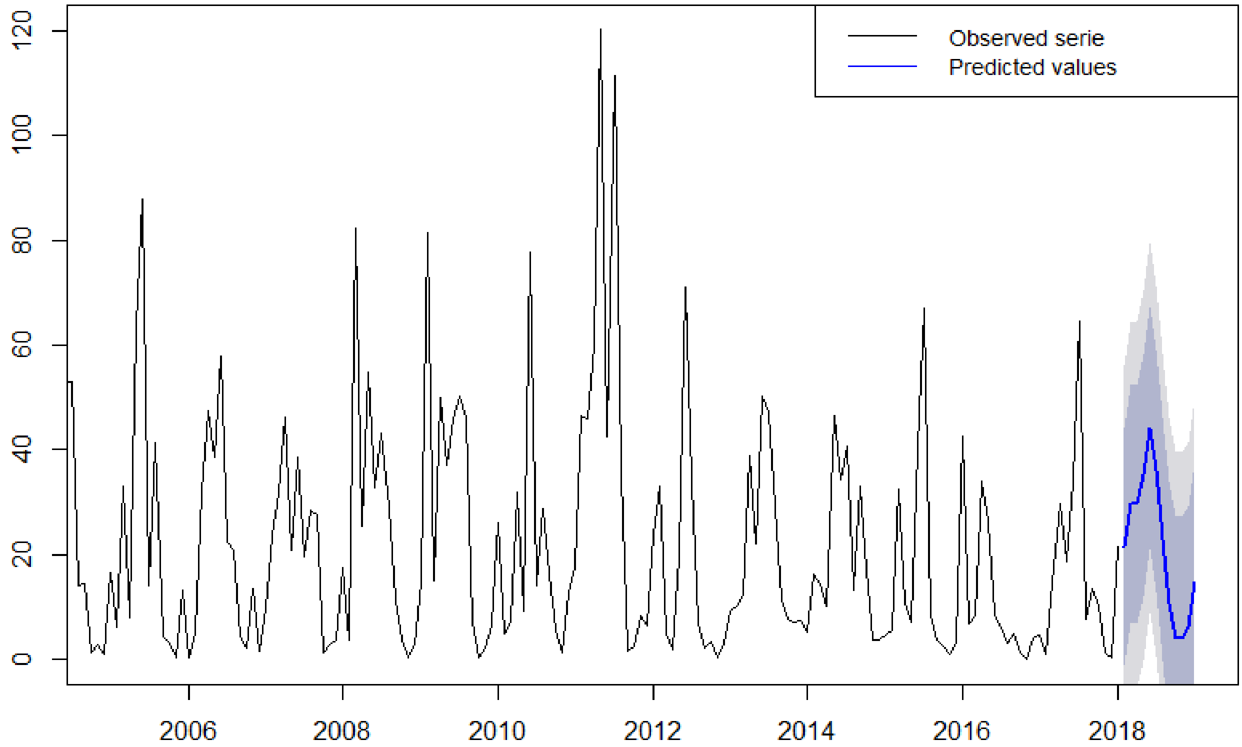

Figure 7: Observed series, predicted values for the accumulated monthly precipitation with 80% and 95% confidence intervals.

On the other hand, the SARIMA model could not accurately estimate the actual rainfall, especially in early 2018, where it rained more than expected by the model for the period (Table 5). The highest observed rainfall was in April, a cumulative total of almost 183 mm of rainfall, while the expected value according to the SARIMA model was only 29 mm of rainfall. According to local press reports, April 2018 recorded more than expected rainfall by the region's regulatory agencies. “Rainfall recorded in the cities of Campina Grande and João Pessoa in Paraíba until Thursday (26) exceeded the average expected for April, according to the Paraiba State Water Management Executive Agency (AESA). The rainfall in Campina Grande exceeded the amount of 156mm, equivalent to over 40% of the historic 111mm value. The data refer to rainfall during the first 25 days of April.” (GERMANO, 2018). As of June 2018, all actual precipitation values have been within the confidence interval with both 80% and 95% confidence, respectively.

Table 5: Observed and estimated values with confidence intervals for the monthly accumulated precipitation between February and December 2018. The highlighted confidence intervals are those in which the observed precipitation belongs to the interval.

Period	**Observed**	**Estimate**	**Confid. Int. (80%)**	**Confid. Int. (95%)**
Fev 2018	77.6	21.37	[0, 43.97]	[0, 55.94]
Mar 2018	65.4	29.63	[6.9, 52.36]	[0, 64.39]
Abr 2018	182.5	29.51	[6.63, 52.39]	[0, 64.51]
Mai 2018	110.2	35.06	[12.01, 58.12]	[0, 70.32]
Jun 2018	34	44.08	**[20.95, 67.2]**	**[8.71, 79.44]**
Jul 2018	38.2	36.03	**[12.87, 59.18]**	**[0.61, 71.44]**
Ago 2018	10.4	22.88	**[0, 46.05]**	**[0, 58.32]**
Set 2018	3.4	10.69	**[0, 33.87]**	**[0, 46.14]**
Out 2018	2.1	3.99	**[0, 27.17]**	**[0, 39.45]**

Nov 2018	2.7	4.02	**[0, 27.2]**	**[0, 39.48]**
Dez 2018	28.7	5.96	**[0, 29]**	**[0, 41.42]**

4. Conclusions

Precipitation in the city of Campina Grande-PB showed high variability during the study period. This variable can be influenced by several climatic and meteorological factors, which makes it difficult to choose a model that can faithfully delineate the behavior of precipitation.

The model was not sensitive to the punctual estimates of the accumulated precipitation in the first months of 2018 since they presented precipitation above the expected average for the period in the region. Given this, the ARIMA (3,0,1) x (2,1,1) 12 model could not fully capture the exogenous variables responsible for the variation in precipitation. On the other hand, the model approached in this study was efficient in the seasonality analysis since it was able to identify and estimate the dry and rainy periods in the region of Campina Grande.

References

Akaike, H. A., 1978 Bayesian analysis of the minimum AIC procedure. Ann. Inst. Statist. Math., 30, 9-14.

Akaike, H., 1998. Information theory and extension of the maximum likelihood principle. In: Selected Papers of Hirotugu Akaike. New York: Springer, 199-213. DOI: https://doi.org/10.1007/978-1-4612-1694-0_15

Bertoni, J. C.; Tucci, C. E. M., 1993. Precipitação. Hidrologia: ciência e aplicação, 2, 177-242.

Bicalho, C. C.; Sáfadi, T.; Charret, I. C., 2014. The influence of climatic factors on dengue epidemies in the cities Cuiabá (Mato Grosso state) and Lavras (Minas Gerais state), Brazil, using statistical methods, Rev. Bras. Biom, 32 (2), 308 – 322.

Box, G. E. P.; Gwilym, M. J.; Gregory, C. R.; Greta, M. L., 2015. Time series analysis: forecasting and control. 5ed. John Wiley & Sons.

Camelo, H. N.; Lucio, P. S.; Leal Junior, J. B. V.; Carvalho, P. C. M., 2018. A hybrid model based on time series models and neural network for forecasting wind speed in the Brasilian northeast region. Sustainable Energy Technologies and Assessments. 28, 65 – 72. DOI: https://doi.org/10.1016/j.seta.2018.06.009

Costa, E. S., 2019. Análise da Série Temporal de Precipitação Total Mensal do Município de Cruz das Almas-BA. UFRB.

Costa, A. S.; Oliveira, V. G.; Pereira, A. R.; Borges, P. F.; Araújo, L. F., 2015. Estudo do Clima na Região do Brejo Paraibano Utilizando Técnicas de Séries Temporais, para Previsão com o Modelo Sarima, Gaia Scientia, 9 (1), 127-133.

Dantas, L. G.; Santos, C. A. C. dos; Olinda, R. A. de., 2015. Tendências anuais e sazonais nos extremos de temperatura do ar e precipitação em Campina Grande–PB. Revista Brasileira de Meteorologia, 30 (4), 423-434.

Dickey, D. A; Fuller, W. A., 1979. Distribution of the estimator for auto-regressive time series with a unit root, Journal of the American Statistical Association, 74, 427-431. DOI: https://doi.org/10.1080/01621459.1979.10482531

Galvincio, J. D.; Pereira, J. A. dos S.; França, L. M. de A.; Lins, T. M. P., 2017. Análise da variação da vegetação dos períodos secos e chuvosos através do savi e albedo de superfície no município de Belo Jardim–PE. REDE-Revista Eletrônica do PRODEMA, 10 (2).

Gastmans, D.; Santos, V.; Galhardi, J. A.; Gromboni, J. F.; Batista, L. V.; Miotlinski, K.; Chang, H. K.; Govone, J. S., 2017. Controls over spatial and seasonal variations on isotopic composition of the precipitation along the central and eastern portion of Brazil. Isotopes in Environmental and Health Studies, 53 (5), 518 – 538. DOI: https://doi.org/10.1080/10256016.2017.1305376

Goossens, C.; Berger, A., 1986. Annual and seasonal climatic variations over the northern hemisphere and Europe during the last century, Annales Geophysicae, 4 (4), 385-400. DOI: http://hdl.handle.net/2078.1/66385

Haylock, M. R.; Peterson, T. C.; Alves, L. M.; Ambrizzi, T.; Anunciação, T. M. T.; Baez, J.; Barros, V. R.; Berlato, M. A.; Bidegain, M.; Coronel, G.; Garcia, V. J.; Grimm, A. M.; Karoly, D.; Marengo, J. A.; Marino, M. B.; Moncunill, D. F.; Nechet, D.; Quintana, J.; Rebello, E.; Rusticucci, M.; Santos, J. L.; Trebejo, I.; Vincent, L. A., 2006. Trends in total and extreme South American rainfall 1960-2000 and links with sea surface temperature. Journal of Climate, 19, 1490-1512.

Henrique, F. de A. N.; Renilson, T. D., 2007. Estimate of reference evapotranspiration in the city of Campina Grande, Paraíba state, Brazil. Revista Brasileira de Engenharia Agrícola e Ambiental, 11 (6), 594-599.

Hounsou-GBO, G. A.; Servain, J.; Araujo, M.; Martins, E. S.; Bourles, B.; Caniaux, G., 2016. Oceanic Indices for Forecasting Seasonal Rainfall over the Northern Part of Brazilian Northeast. American Journal of Climate Change, 5, 261 –

274.DOI: http://dx.doi.org/10.4236/ajcc.2016.52022
Germano, E., 2018. Chuvas ultrapassam média esperada para o mês de abril em JP e CG. Jornal da Paraíba. 26 de Abril de 2018. Available at: http://www.jornaldaparaiba.com.br/vida_urbana/chuvas-ultrapassam-media-esperada-para-o-mes-de-abril-em-jp-e-cg.html. Accessed October 4, 2019.
Kendall, M. G. Rank correlation methods. London: Charles Griffin, 1975.
Liska, G. R.; Bortolini, J.; Sáfadi, T.; Beijo, L.A., 2013. Estimativas da velocidade máxima de vento em Piracicaba – SP via séries temporais e teoria de valores extremos. Rev. Bras. Biom., 31 (2), 295 – 309.
Ljung, G. M.; Box, G. E. P., 1978. On a measure of lack off it in time series models. Biometrika, 65, 297-303.DOI: https://doi.org/10.1093/biomet/65.2.297
Lucio, P. S.; Silva, F. D. dos S.; Fortes, L. T. G.; Santos, L. A. R.; Ferreira, D. B.; Salvador, M. A.; Balbino, H. T.; Sarmanho, G. F.; Santos, L. S. F.; Lucas, E. W. M.; Barbosa, T. F.; Dias, P. L. S., 2010. Um modelo estocástico combinado de previsão sazonal para a precipitação no Brasil. **Rev. bras. meteorol.**, São Paulo, 25 (1), 70 – 87. DOI: http://dx.doi.org/10.1590/S0102-77862010000100007
Marengo, J. A.; Valverde, M. C., 2007. Revista Multiciência, v. 8.
Marengo, J. A., 2010. Vulnerabilidade, impactos e adaptação à mudança do clima no semiárido do Brasil. Parcerias estratégicas, 13 (27), 149-176.
Minuzzi, R. B., 2017. Probabilidade de transição e condicional para chuva mensal e extremos diários em Santa Catarina. Ceres, 63 (6).
Murat, M.; Malinowska, I.; Gos, M.; Krzyszczak, J., 2018. Forecasting daily meteorological time series using ARIMA and regression models. Int. Agrophys. 32 (2), 253 – 264. DOI: https://doi.org/10.1515/intag-2017-0007
Nisar, N.; Badar, N.; Aamir, U. B.; Yaqoob, A.; Tripathy, J. P.; Laxmeshwar, C.; Munir, F.; Zaidi, S. S. Z., 2019. Seasonality of influenza and its association with meteorological parameters in two cities of Pakistan: A time series analysis. Plos One. 14 (7), 1 – 13. DOI: https://doi.org/10.1371/journal.pone.0219376
Oliveira, M. R. G.; Cantalice, J. R. B.; Ferreira, T. A. E.; Filho, M. C.; Cruz, D. V.; Falacão, A. P. S. T., 2015. Estudo estatístico do coeficiente de escoamento da bacia hidrográfica do Riacho Jacu no Sertão do Pajeu – PE. Rev. Bras. Biom, 33 (3), 277 – 290.
Pereira, A. R.; Costa, A. S.; Oliveira, V. G.; Borges, P. F.; Filho, A. I., 2015. Análise do comportamento das médias anuais da precipitação pluvial e temperatura da cidade de Areia, Paraíba. Gaia Scientia, 9 (1). DOI: http://www.periodicos.ufpb.br/ojs2/index.php/gaia/article/view/24080/13287
Phillips, P. C. B.; Perron, P., 1988. Testing for a unit root in time series regression. Biometrika, 75, 335–346.DOI: https://doi.org/10.1093/biomet/75.2.335
R Development Core Team., 2018. R: A language and enviroment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria, available at: http://cran.r-project.org/index.html
Rao, V. B.; Franchito, S. H.; Santo, C. M. E.; Gan, M. A., 2016. Na update on the rainfall characteristics of Brazil: seasonal variations and trens in 1979-2011. International Journal of Climatology, 36 (1), 291 – 302. DOI: https://doi.org/10.1002/joc.4345
Rocha, J. V. de C., 2011. Modelagem de dados meteorológicos da cidade de Recife utilizando a metodologia da análise de séries temporais. Dissertação de mestrado (Mestre em Desenvolvimento de Processos Ambientais) – Universidade Católica do Pernambuco, Recife.
Rocha, L. C. B.; Bernardo, S. de O., 2002. Uma revisão da dinâmica das chuvas no nordeste brasileiro. Revista Brasileira de Meteorologia, 17 (1), 1-10.
Santos, , C. A. C.; Brito, J. I. B., 2007. Análise dos índices de extremos para o semi-árido do Brasil e suas relações com TSM e IVDN. Revista Brasileira de Meteorologia, 22, 303-312.
Shapiro, S. S.; Wilk, M. B., 1965. An analysis of variance test for normality (complete samples). Biometrika, 52, (3/4), 591-611. DOI: https://doi.org/10.1093/biomet/52.3-4.591
Sharma, P.; Chandra, A.; Kaushik, S. C., 2009. Forecasts using Box–Jenkins models for the ambient air quality data of Delhi City, Environ Monit Assess, 157, 105 – 112.
Stagge, J. H.; Tallaksen, L. M.; Gudmundsson, L.; Loon, A. F. V.; Stahld, K., 2016. Response to comment on “Candidate Distributions for

Climatological Drought Indices (SPI and SPEI)". Int. J. Climatol. 36, 2132 – 2138. DOI: https://doi.org/10.1002/joc.4564

Tablada, C. J.; Ramirez, F. A. P.; Vieira, G. I. A.; Vasconcelos, J. M. 2016. Modelagem e previsão de exportações do Brasil fazendo uso de séries temporais. Rev. Bras. Biom. 34 (1), 33 – 48.

Wald, A.; Wolfowitz, J., 1943. An exact test for randomness in the non-parametric case based on serial correlation. The Annals of Mathematical Statistics, 14 (4), 378-388.

Xavier, E. F. M.; Barbosa, N. F. M.; Júnior, S. F. A. X., 2018. Análise da Produção Brasileira de Biodiesel por meio de Séries Temporais, Gaia Scientia, 12 (3), 1-13.