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Time Series Analysis of Urban Forest Waste in João Pessoa (Northeast Brazil)

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Abstract. Urban afforestation requires management to ensure its sustainability within the city, and urban pruning waste is generated regularly throughout the year. This paper analyzed the time series of the urban pruning waste volume for João Pessoa (Northeast Brazil) from January 2008 to December 2014, with the objective of determining the volume of urban pruning waste generated and adjusting it to a forecast model. The models studied were part of the ARIMA (Autoregressive Integrated Moving Average) Family. The main results indicated that the ARIMA family models presented satisfactory results for the forecast, and ARIMA (0,1,4) was the model that provided the best forecast for 2014. This study contributes with a better understanding of the pattern and amount of urban pruning waste generated in João Pessoa and could assist the future orientation of municipal public policies.

Keywords. ARIMA; Biomass; Forecasting; Forest Economy.

INTRODUCTION

Urban afforestation refers to a pattern of distribution of trees in urban territories, public roads, and remaining areas that do not contain buildings; the success of urban afforestation depends on adequate and judicious planning (Bobrowski and Biondi 2012). Correction of unstructured and disorganized afforestation includes pruning and removal (or substitution) of trees. Pruning is the elimination of leaves, branches, buds, and foliage for compatibility with the existent physical space or to promote appropriate development of the plant. Pruning can be used for cleaning, correction, adequacy, lifting, and emergency purposes (RECIFE 2013; SVMA 2015).

Maintenance of urban afforestation encompasses green areas (parks, squares, and gardens) and streets (public roads), and its maintenance includes irrigation, supplemental fertilization, preventive treatment, and pruning. Urban afforestation requires constant maintenance activities to ensure its sustainability within the city, and its management results in a significant amount of urban pruning waste (UPW), which includes urban tree and woody yard residues (Araújo et al. 2018; Araújo et al. 2019). In 2014, Brazil produced 78.6 t of municipal solid waste (MSW), which included residential and urban cleaning wastes (residues from street sweeping, management of municipal gardens and parks, and urban pruning). The state of Paraiba (Northeast Brazil) generated 1.278 t of MSW in 2014, with an average of 3,504 t/day (ABRELPE 2014).

According to the Brazilian National Environmental Sanitation Information System (SNSA 2016), the percentage of UPW within MSW varied between 1.41% and 9.37% in 2014. The municipality of João Pessoa generated 415,960 t of MSW in 2013, which included domestic, construction, and street cleaning wastes. Urban pruning and replacement of trees was responsible for 28,710 t, corresponding to 6.9% of all MSW collected (Prefeitura de João Pessoa 2014). As UPW is generated regularly throughout the year due to scheduled maintenance operations on urban afforestation, this frequency over time can be classified as a time series, which is defined as a set of observations of a variable arranged sequentially in time (Andrade 2013).

The analysis of temporal series is an important instrument to understand the market and to formulate action plans and strategies. The history of a variable can interfere on its behavior and generate information on probable future behavior through the construction of models that predict the future movements (Fischer 1982; Rezende et al. 2005; Coelho Jr., Melquíades, et al. 2018). The use of time series forecasting models is an alternative in the decision-making process, involving activities that require planning, policy evaluation, and reduction of uncertainties. Time series forecast models present wide applicability, with different resources and knowledge fields such as administration, economics, forestry, and health sectors to name a few (Bressan 2004; Coelho Jr., Rezende, Sáfadi, et al. 2006; Antunes and Cardoso 2015).

In the forestry sector, there are several applications of time series analysis: Floriano et al. (2006) developed height growth equations in a population of *Pinus elliottii*; Coelho Jr., Rezende, Calegario, et al. (2006) forecasted charcoal prices in the state of Minas Gerais; Soares et al. (2008) forecasted natural rubber prices in the domestic market; Coelho Jr. et al. (2009) forecasted natural rubber prices in the international market; and Almeida et al. (2009) forecasted the price paid for exports of wood composites from the Paraná state, where graphical analysis and statistics indicated the Autoregressive Integrated Moving Average (ARIMA)(1,1,3) as the best fit to wood composite price series. Finally, Soares et al. (2010) elaborated a model to forecast the price of standing timber for *Eucalyptus* spp.

Decision makers and urban afforestation managers that wish to carry out reliable predictions of the amount of urban pruning waste are usually faced with limited budget for its maintenance. Urban forestry management techniques can generate these data, providing significant elements for the prediction of future behavior. However, there are limited data on the forecast of woody residues from urban pruning activities. The study presented herein analyzed the forecast model for urban pruning waste in the municipality of João Pessoa, Paraíba.

MATERIALS AND METHODS

Study Object

This study utilized the UPW historical series in tonnes (t) for João Pessoa, collected monthly by the Municipal Urban Cleaning Autarchy (EMLUR). The period analyzed was January 2008 to December 2014, encompassing 84 data sets. Data between January 2008 and December 2013 were utilized to adjust the model, and data between January and December 2014 were utilized to validate the model.

Time Series Analysis

A specific time series $\{Y_t, t = 1, 2, 3, ..., n\}$ is defined as a set of observations of a variable, sequentially arranged in time (Morettin and Toloi 2006). Wold (1938) affirmed that a temporal series presents the following components: trend (T), seasonality (S), and irregular or random variations (a_t). When observing a variable (Y) that evolves in time (t), combined actions determine these movements, in which $Y_t = f(T_t, S_t) + a_t$, where the trend (T_t) is the result of a complex of causes in which the series of prices acts continuously in the same sense throughout time. Seasonality (S) is the fluctuation caused, with specific regularity, within the annual period and can be caused by climatic variations, for example. The random or irregular component (a_t) is caused by exogenous factors, including catastrophic factors, such as war and epidemics, government plans, and random factors. The values of a_t represent a sequence of random and independent shocks, and a_t is a noncontrollable portion of the model, usually referred to as white noise.

The Autoregressive Integrated Moving Average (ARIMA), introduced by Box and Jenkins (1976), is based on the idea that a nonstationary time series, homogeneous, can be modeled from (d) differentiations with the addition of an autoregressive component (p) and an average moving component (q). Considering that (B) is a difference operator (i.e., $B = Y_t - Y_{t\text{-}1}$), $\{Y_t\}$ is a process that can be described by an ARIMA model (P,D,Q), and data backward (B) are the lag times or lag, in time (sequence), as follows:

$$Ø_p\,(B)Z_t = \Theta_0 + \Theta_q(B)a_t$$

$$Z_t = \begin{cases} Y_t, & \text{if the process is stationary, when } d = 0 \\ (1 - B)^d Y_t, & \text{if the process is nonstationary, when } d \geq 1 \end{cases}$$

The pondering of differentiation Y_t corresponds to an ARIMA model (p,d,q) with:

$$Ø_p\,(B)(1 - B)^d Y_t = Ø_0 + Ø_q(B)a_t$$

$Ø_p(B) = 1 - Ø_1B - Ø_2B^2 - ... - Ø_pB^p$ is the autoregressive component of p order (AR [p]), $Ø_0 = \mu(1 - Ø_1 - Ø_2 - ... - Ø_p)$ is the intercept or constant, μ is a periodic deterministic function (mean), and

$\Theta_q(B) = 1 - \Theta_1 B - \Theta_2 B^2 - \ldots - \Theta_q B^q$ and is the moving average operator of q order (MA[q]), which is a white noise process. If constant ϑ_0 is different from zero, the integrated series provides a deterministic trend (i.e., the series presents an increasing or decreasing trend, which is independent of random disturbances)(Pindyck and Rubenfield 1991).

For the verification of the stationarity of the model, visual analysis and decomposition of the time series were carried out. The Augmented Dickey-Fuller test (ADF)(Dickey and Fuller 1981) was applied to verify the stationarity of the series, along with the Phillips-Perron test (PP)(Phillips and Perron 1988) and the Kwiatkowski-Phillips-Schmidt-Shin test (KPSS) (Kwiatkowski et al. 1992). These tests verify whether series y_t presents a unit root and, consequently, if stationarity is confirmed.

The identification of the model consists of determining its order based on the “principle of parsimony.” This step is the most critical for the use of the model and determines the types of generator model series:

$$y_t \left| \begin{array}{l|l|l} \text{AR} & & (p) \\ \text{MA} & \text{What is the order of the} & (q) \\ \text{ARMA} & \text{model, i.e., what are the} & (p, q) \\ \text{ARIMA} & \text{values of} & (p, d, q) \\ \text{SARIMA} & & (p, d, q) \times (P, D, Q)_s \\ \vdots & & \end{array} \right.$$

To assist in this identification step, time domain analysis was utilized (Box and Pierce 1970), which is the fundamental approach for the analysis of time series. After identification and selection of the appropriate model, process parameters (AR) and (MA) were estimated. Parameter estimates were obtained from the Gaussian distribution for the maximum likelihood method, for all possible combinations, to fulfill the conditions of invertibility and uniqueness for the parameters.

Standardized residues, residues of autocorrelation function (ACF), residues of partial autocorrelation function (PACF), and portmanteau’s test (Dickey and Fuller 1981) were analyzed to verify whether the model proposed was white noise:

$$Q_k = n \sum_{l}^{k} c_k^2$$

n = number of observations; k = number of lags; and c_k = autocorrelation of residuals. The model is accepted if $Q \leq \chi^2$ (λ, $k - n$), where χ^2 is the chi-square, λ is the significance level (with a 95% confidence interval), k the lag order, and n the number of parameters.

Another way to verify the model utilizes the Akaike’s Information Criterion (AIC):

$$AIC = -2\ln(L) + 2(p + q)$$

L = maximum likelihood; p and q = model parameters to obtain the minimum AIC value (Akaike 1977). After the iterative process of identifying, estimating, and checking the model, if the model can provide an estimate of the series that satisfactorily adjusts to real data, this model can be used to forecast variable values. Forecasting processes, based on time series models, are procedures that aim to extend (to future values) the model described and adjusted to the present and past values of the variable. Therefore, forecasts enable determination of the expected value of a future observation.

The mean square error (MSE) was calculated for the forecasts obtained, enabling comparison between forecasted and observed values for the adjusted series and further selection of the model with lowest MSE (Soares et al. 2010).

$$MSE = \frac{\Sigma(y_t - y_t^e)^2}{n}$$

RESULTS AND DISCUSSION

Figure 1 shows the evolution and behavior of the urban pruning waste mass series for João Pessoa (MPA-JP) and the logarithmic series (Ln [MPA-JP]) from January 2008 to December 2013, expressed in 1,000 tons. The napierian logarithm was necessary to stabilize the variance while preserving the properties of the series data. MPA-JP presented an estimated average of 2,151 tons, a median of 2,115 tons, a minimum value of 1,256 tons, and a maximum value of 2,772 tons.

Analysis of Figure 1 reveals an increasing trend for the MPA-JP series over time, which provides indications of nonstationary character. It can also be observed that the mass of UPW increased in the period between April and July in comparison with the other months of the year. This occurred due to the rainy season in the city, increasing the occurrences of broken branches and fallen trees. It is also worth noting that when the mass of UPW generated annually is analyzed, the demand of the population for the

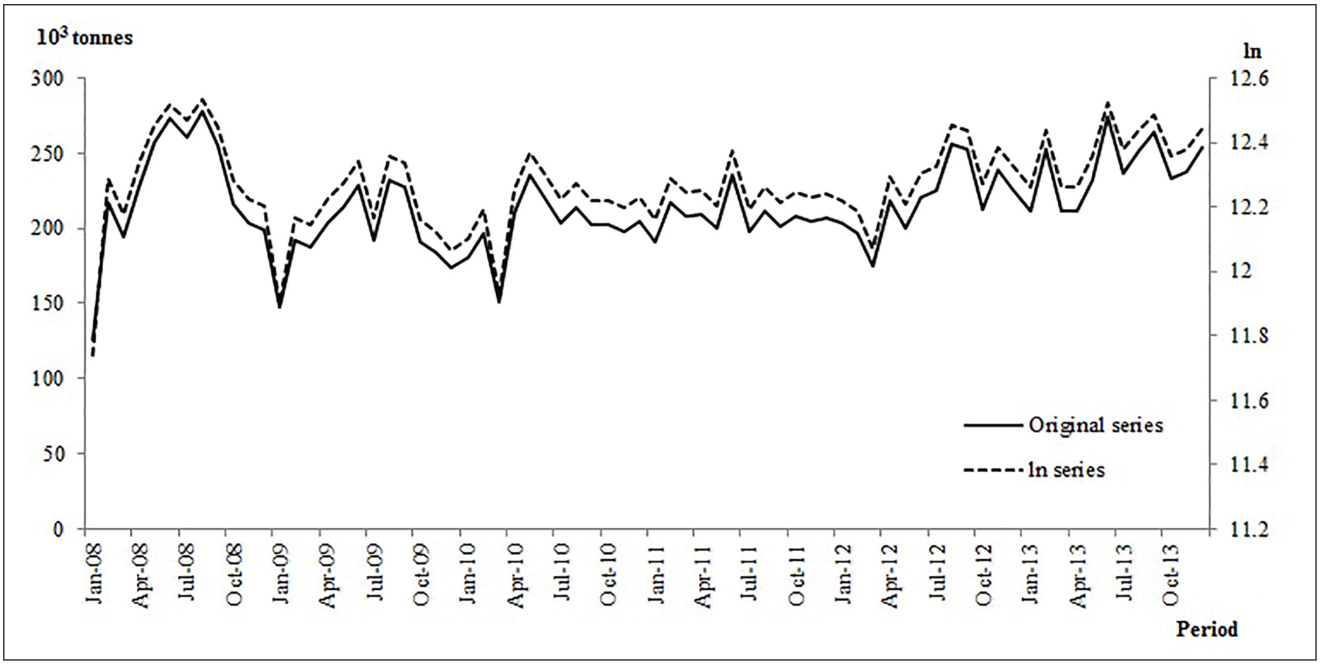

Figure 1. Evolution of the original series (10^3 tonnes) and logarithmized (Ln) series for urban pruning waste in João Pessoa, from 2008 to 2013.

service must also be considered (specific requests to the competent agency for the execution of pruning and removal of woody debris). The waste management policy for woody debris/UPW, enforced by the government, also influences the annual mass generated through hiring or lay-offs of personnel, administrative changes, reviewing and amendment of contracts with service providers, to name a few.

Figure 2 shows the decomposition of data, trends, seasonality, and waste of Ln (MPA-JP) from January 2008 to December 2013. Data decomposition revealed the presence of trend and seasonal components that must be inferred within the model. In Figure 2, low gray bars indicate the predominance of the component, and higher heights indicate a predominance of the component of MPA-JP decomposition. Visual inspection and series decomposition cannot, on their own, confirm the stationarity of the Ln (MPA-JP). Therefore, the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests were applied to verify the presence of unit root, as shown in Table 1.

The ADF test shows the presence of stationarity when there is rejection of the null hypothesis (H0) or when the series presents a unit root. Alternative hypothesis (H1) refers to the nonstationarity of the series and does not incur in the unit root region. The ADF test shows that, if $|\alpha| < |t|$, H0 is accepted (where α is the significance level). Thus, Ln (MPA-JP) at 5% significance level accepts H0, due to the presence of a unit root (i.e., nonstationary, requiring transformation by the first difference to be stationary).

Application of the ADF test to the first differential of the 1ºDiff(Ln [MPA-JP]) revealed that, for the significance levels studied, the value of t was higher than any of the critical values. It can be concluded that there is no unit root, and therefore 1ºDiff(Ln [MPA-JP]) is stationary. The KPSS test states that the null hypothesis is the nonexistence of a root unit, and (Ln [MPA-JP]) presented t = 0.40, which was higher than the 10% critical value for the test. This demonstrated the rejection of the null hypothesis, showing that the (Ln [MPA-JP]) is not stationary. For the 1ºDiff(Ln [MPA-JP]) with t = 0.09, which was lower than any of the critical values, a possible stationarity is characterized. The PP test of 1ºDiff(Ln [MPA-JP]) confirmed stationarity, with t = -13.98, well above t = -6.29 for MPA-JP.

Figure 3 shows the identification of the order of the model using autocorrelation functions (ACF) and partial autocorrelation functions (PACF) for Ln (MPA-JP).

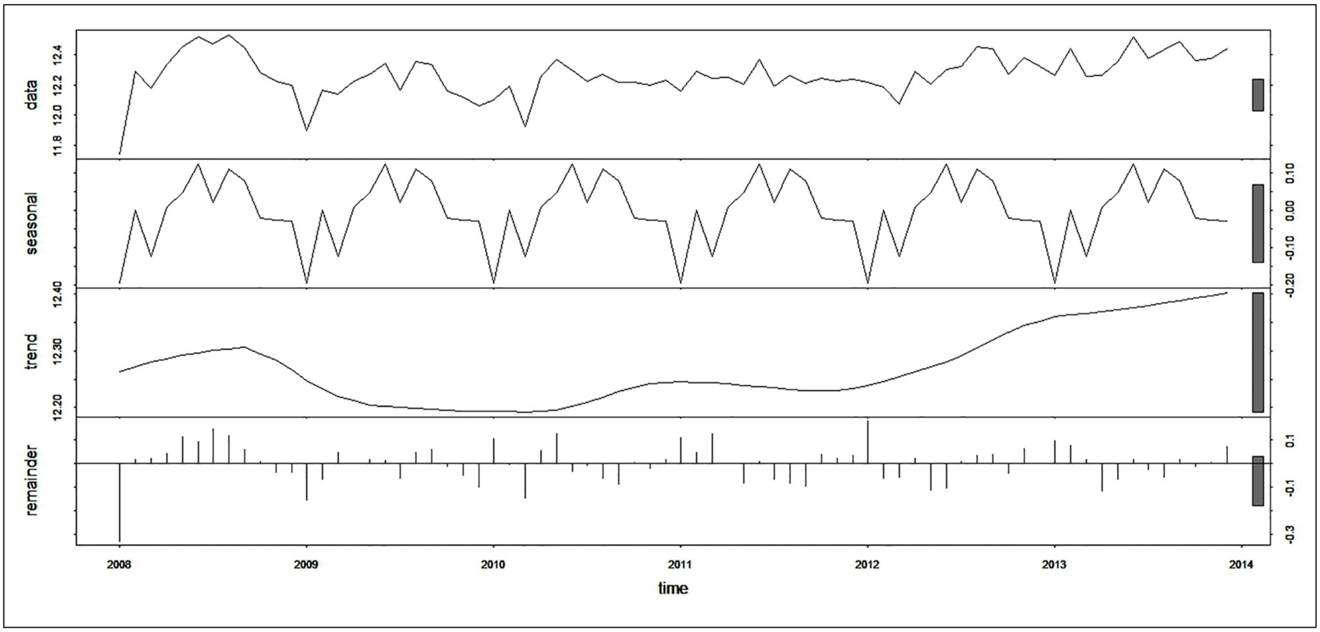

Figure 2. Data decomposition, trend, seasonality, and residues for Ln (MPA-JP) from January 2008 to December 2013.

Table 1. Unit root tests for Ln(MPA-JP) and its first differential, 1ºDiff[Ln(MPA-JP)].

	Ln(MPA-JP)				1ºDiff[Ln(MPA-JP)]			
Test	**1%**	**5%**	**10%**	***t***	**1%**	**5%**	**10%**	***t***
ADF	-4.04	-3.45	-3.15	-3.41	-4.04	-3.45	-3.15	-8.08
KPSS	0.73	0.46	0.34	0.4	0.73	0.46	0.34	0.09
Phillips-Perron	-4.09	-3.47	-3.16	-6.29	-4.09	-3.47	-3.16	-13.98

t = student's *t*-test

It is observed that the ACF graph decreases quickly after lag4, indicating that the series cannot be stationary and does not present seasonal behavior over time. This justifies the need of first order differentiation for the series to be stationary. As no cut is observed after lag1, this suggests MA (0). The PACF graph only indicates significances for lag1 and lag2, indicating AR (2) order autoregressive terms. The ARIMA (2,1,0) model was consequently identified. However, according to Meyler et al. (1998), interpretation of the autocorrelation (ACF) and partial autocorrelation (PACF) graphs can be difficult, and identification of the models by the Box-Jenkins methodology involves subjectivity.

After identification of the ARIMA (2,1,0) model, the order was limited at maximum of five discrepancies per autoregressive processes (AR [p = 5]) and five discrepancies for moving averages processes (MA [q = 5]). A sample space of 33 ARIMA models (p,d,q) was considered. Of the 33 models considered, only 24 presented white noise, verified by the Box-Pierce test, with $Q(m) < x^2_\alpha$. When the residual values were graphically checked by the tsdiag function (x) in R, only 12 models were detected as white noise, being selected for forecast analysis. The ARIMA (2,1,0) model initially selected did not fulfill the criteria adopted. Of the 12 models selected after verification of white noise, only 4 presented significant values at 80% and 95% significance levels. Table 2 shows the results of the models for the AIC and Box-Pierce tests.

Forecasts were carried out for the models depicted in Table 2, and calculation of the mean squared prediction error (MQPE) indicated the most appropriate. Table 3 shows the forecasts for the amount of UPW in

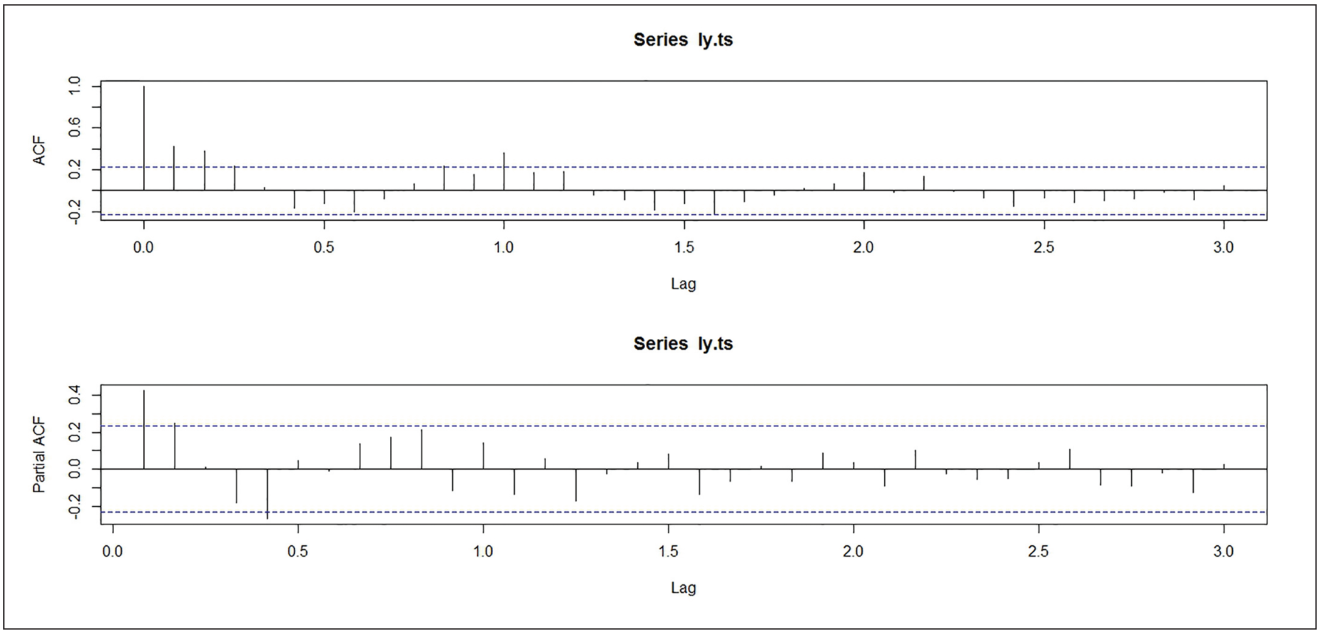

Figure 3. Autocorrelation function (ACF) and partial autocorrelation function (PACF) of Ln (MPA-JP).

João Pessoa from January to December 2014. The ARIMA (0,1,4) model presented the lowest MQPE for 2014 and therefore was selected. The ARIMA (0,1,4) model was selected for all 12 periods, and its shape is characterized by:

$$Y_t = \frac{(1 + \Theta_1 B + \Theta_2 B^2 + \Theta_3 B^3 + \Theta_4 B^4)\alpha_t}{(1 - B)}$$

Therefore, the model with its coefficients is characterized by:

$$Y_t = \frac{(1 - 0.4750 + 0.2984 + 0.2909 - 0.0265)\alpha_t}{(1 - B)}$$

Figure 4 shows the residual values of the ARIMA (0,1,4) model. Besides the Box-Pierce test, the correlogram suggests independence of residuals for several lags, where the control limits of the AFC graph corroborate the adequacy of the selected model. It was decided to forecast values for 12 months, i.e., throughout 2014. Figure 5 shows the behavior of the forecast, considering 80% and 95% confidence intervals, beside the observed values for 2014 in months. The model presented satisfactory forecasts, with MQPE = 3.10.

Table 2. Preselected models for the forecast of urban pruning waste in João Pessoa.

			Test Box-Pierce	
	ARIMA (p,d,q)	AIC	Q (m)	χ^2_α
1	(5,1,0)	-90.317	0.2247	40.979
2	(1,1,2)	-91.072	0.1802	44.687
3	(0,1,3)	-91.92	0.1462	46.05
4	(0,1,4)	-89.951	0.1048	46.938

Regarding some reflections on the potentiality for urban pruning residues to be used as secondary raw materials, pruning waste can be used as a bulking agent for the composting of dewatered wastewater sludge (Ponsá et al. 2009), for the production of kraft paper (Gencer 2015), as a component in soilless growing media (Benito et al. 2005), and for the production of xylitol (Albuquerque et al. 2014). In Malaysia, pruning waste is currently left to rot or incinerated, but Lim et al. (2007) verified that utilization of pruning waste for energy purposes could lead to an increase in the contribution of biomass to the nation's energy consumption to approximately 59%. In China, the use of green waste from tourist attractions for renewable energy production presents high potential, with Shi, Du, et al. (2013) discussing this potential and policy implications. Still, in China, the potential challenges and development of pruning

Table 3. Observed and expected values (tons) for the ARIMA (*p,d,q*) models for the year 2014 (January to December) for urban pruning waste in João Pessoa.

Period	Observation	ARIMA (5,1,0)	ARIMA (1,1,2)	ARIMA (0,1,3)	ARIMA (0,1,4)
Jan-14	223,749	237,694	236,435	236,281	236,480
Feb-14	260,281	240,409	242,444	241,370	242,222
Mar-14	214,331	250,639	244,362	245,715	246,776
Apr-14	248,316	243,005	244,967	245,715	246,212
May-14	279,881	241,643	245,158	245,715	246,212
Jun-14	327,756	248,530	245,217	245,715	246,212
Jul-14	255,385	243,984	245,236	245,715	246,212
Aug-14	277,618	242,505	245,241	245,715	246,212
Sep-14	248,623	246,350	245,244	245,715	246,212
Oct-14	238,390	244,629	245,244	245,715	246,212
Nov-14	257,962	242,983	245,244	245,715	246,212
Dec-14	170,095	245,531	245,244	245,715	246,212
MQPE		4.62	4.36	3.81	3.1
Error (%)		-2.5	-2.4	-2.25	-2.03

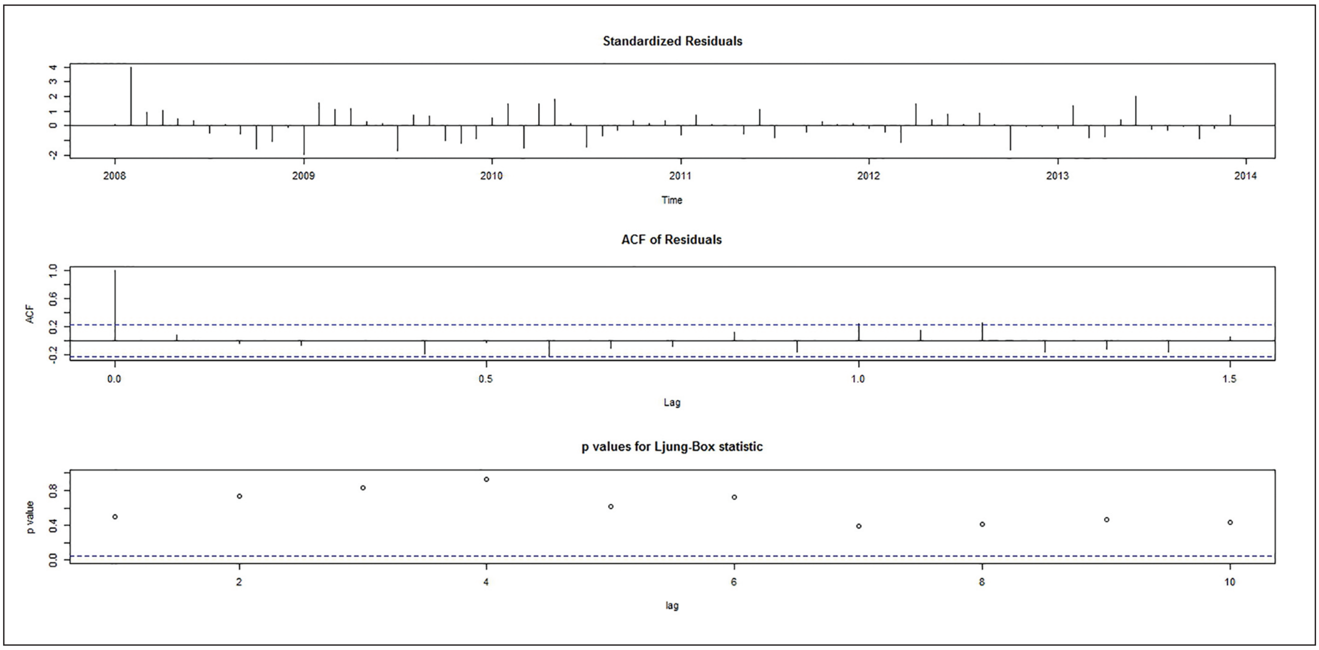

Figure 4. ARIMA (0,1,4) model residuals for Ln(MPA-JP).

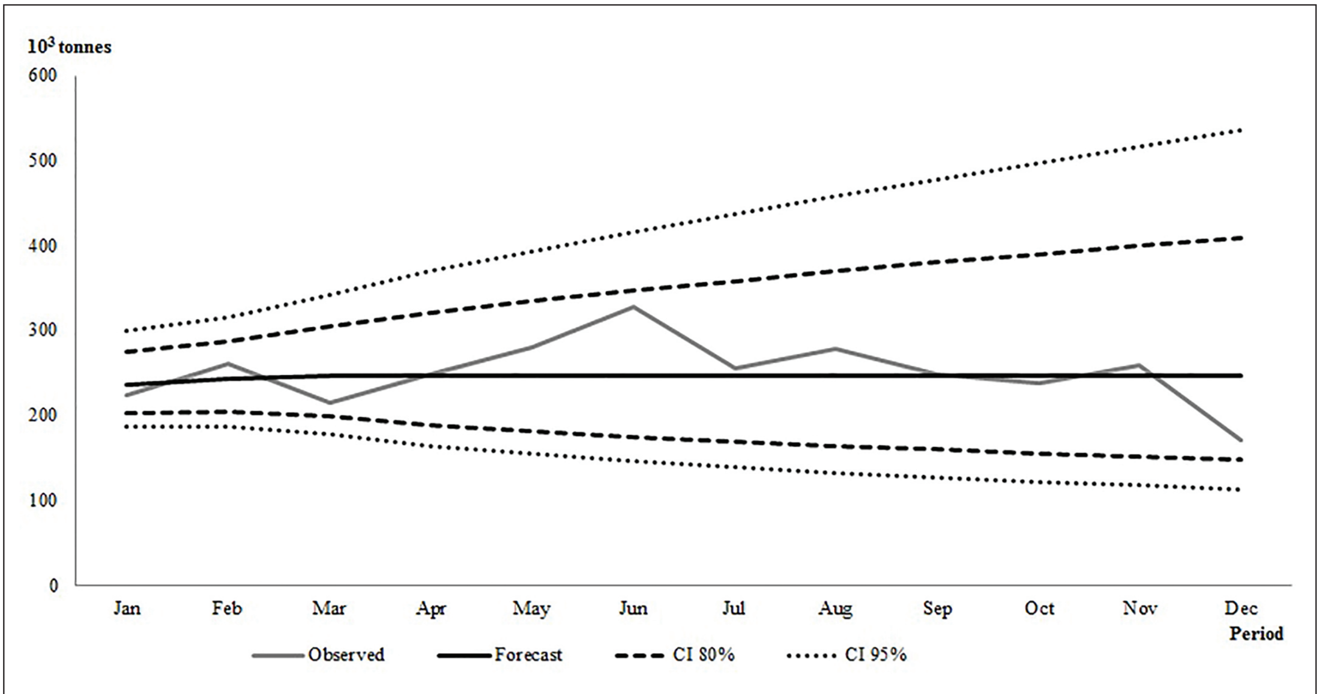

Figure 5. Forecast of UPW mass for João Pessoa in 2014 (1,000 tonnes).

waste for renewable and sustainable energy production was reported by Shi, Ge, et al. 2013.

This study contributes with a better understanding of the pattern and amount of urban pruning waste generated in João Pessoa. The results presented herein can be utilized in energy optimization studies incorporating urban pruning residue as an energy utility available for heat or electricity production (such as in Lozano et al. 2009; Carvalho et al. 2011; Carvalho et al. 2012; Carvalho et al. 2014; Romero et al. 2014; Millar et al. 2015; Carvalho, Delgado, et al. 2016; Romero et al. 2016; Delgado et al. 2018; Carvalho, Melo, et al. 2019), and to develop Life Cycle Assessment studies with the purpose of confirming positive environmental effects derived from biomass-based electricity or heat (such as in Carvalho, Silva, et al. 2016; Carvalho and Delgado 2017; Araújo et al. 2018; Coelho Jr., Martins, et al. 2018; Grilo et al. 2018; Carvalho, Segundo, et al. 2019; Melo et al. 2019). In summary, the use of urban pruning residue for energy purposes presents three advantages: (i) achieve compliance with the Kyoto Protocol; (ii) reduce dependence on fossil fuels; and (iii) manage urban afforestation in a sustainable way. The derived economic benefits can be directed towards better maintenance of urban afforestation, following a circular economy approach.

CONCLUSION

Considering the scenario herein, it was concluded that the ARIMA family models presented satisfactory results for the forecast of urban pruning waste generated in João Pessoa (Northeast Brazil). The ARIMA (2,1,0) model initially identified by autocorrelation and partial autocorrelation functions did not produce appropriate adjustments. For the sample space constituted by 33 models, and limited to 5 discrepancies for moving averages processes and 5 discrepancies for the autoregressive component, the ARIMA (0,1,4) model provided the best forecast for all 12 time periods for the urban pruning waste mass in João Pessoa, presenting the lowest mean squared prediction error. This study provided better understanding of the behavior of urban pruning waste generation in João Pessoa, and this information can be utilized for the planning of public policies.

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Résumé. Le boisement urbain requiert de l'organisation afin d'assurer sa pérennité au sein de la ville et la production de résidus d'élagage qui en découle est constante durant toute l'année. Cette recherche a analysé la progression temporelle du volume des résidus ligneux urbains pour la ville de João Pessoa (nord-est du Brésil) pour la période de janvier 2008 à décembre 2014 avec comme objectif de déterminer le volume des résidus ligneux urbains générés et de d'établir un modèle prévisionnel. Les modèles examinés étaient de la famille ARIMA (Moyenne mobile intégrée autorégressive). Les principales conclusions indiquèrent que les modèles de type ARIMA montraient des résultats satisfaisants pour la prévision et que ARIMA (0,1,4) était celui fournissant la meilleure prévision pour l'année 2014. Cette recherche contribue à une meilleure compréhension de la structure et de la quantité des résidus ligneux urbains générés à João Pessoa et peut aider à déterminer l'orientation future des politiques publiques municipales.

Zusammenfassung. Die urbane Aufforstung erfordert ein Management zur Sicherstellung seiner Nachhaltigkeit innerhalb der Stadt und urbaner Grünschnitt wird über das ganze Jahr generiert. Die Studie analysiert die Zeitfolge des urbanen Grünabfallvolumens in João Pessoa (Northeast Brazil) von Januar 2008 bis Dezember 2014, mit dem Fokus auf Bestimmung des generierten Grüpnabfallvolumens und der Anpassung an ein Vorhersagemodell. Die untersuchten Modelle waren teil der ARIMA (Autoregressive Integrated Moving Average) Familie. Die hauptresultate zeigten, das ARIMA Familienmodelle befriedigende Eregebnisse für die Vorhersage ergaben und ARIMA (0,1,4) war das Modell, welches die beste Vorhersage für 2014 lieferte. Diese Studie führt zu einem besseren Verständnis der Muster und der Menge des generierten urbanen Grünabfalls in João Pessoa und könnte die zukünftige Orientierung der öffentlichen Verwaltungspolitik unterstützen.

Resumen. La forestación urbana requiere gestión para asegurar su sostenibilidad dentro de la ciudad y los residuos de poda urbana se generan regularmente durante todo el año. Este documento analizó la serie temporal del volumen de residuos de poda urbana para João Pessoa (noreste de Brasil) de enero de 2008 a diciembre de 2014, con el objetivo de determinar el volumen de residuos de poda urbana generados y ajustarlos a un modelo de previsión. Los modelos estudiados formaban parte de la familia ARIMA (Autoregressive Integrated Moving Average). Los principales resultados indicaron que los modelos de la familia ARIMA presentaron resultados satisfactorios para la previsión y ARIMA (0,1,4) fue el modelo que proporcionó la mejor previsión para 2014. Este estudio contribuye con una mejor comprensión del patrón y la cantidad de residuos de poda urbana generados en João Pessoa y podría ayudar a la orientación futura de las políticas públicas municipales.