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Modeling and forecasting blackberry production in Colombia using a Box Jenkins ARIMA approach

Un modelo Box Jenkins ARIMA para modelar y pronosticar la producción de mora de castilla en Colombia

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Abstract

Blackberry production in Colombia contributes to the nation´s gross domestic profit, employment and farmers' social well-being. It is considered of great economic importance as blackberry fruits are used as raw material for the agroindustry. In this manner, production instability affects farmers' economic profitability; therefore, forecasting plays an important role in monitoring production as well as in farmers´ planting decision and resource allocation. Hence, the purpose of the study was to model and forecast blackberry production in Colombia using a Box Jenkins ARIMA approach for the period 1992-2023. A quantitative, non-experimental, correlational and descriptive research design was selected. The appropriateness of the model and its predictive capacity was assessed by verifying the different goodness-of-fit criteria. Results showed that the ARIMA (1,1,0) was the most suitable model as it captured the behavior of the actual time series. Based on the forecasted values it is expected a 5.47% increase in blackberry production for the period 2021-2023 which will consequently improve farmers´ income and thus contribute to the reduction in poverty.

Keywords: Predictive capacity; univariate analysis; data modeling; production.

Resumen

La producción de mora de castilla en Colombia contribuye al producto interno bruto, al empleo y al bienestar social de los agricultores del país. Es considerado de gran importancia económica una vez que los frutos de la mora son utilizados como materia prima para la agroindustria. De esta manera, la inestabilidad de la producción afecta la rentabilidad económica de los agricultores; por lo tanto, el pronóstico de la producción de mora posee un importante papel en la asignación de recursos y la toma de decisiones de los agricultores. Por lo tanto, el propósito del estudio fue modelar y pronosticar la producción de mora en Colombia utilizando un enfoque ARIMA de Box Jenkins para el período 1992-2023. Se seleccionó una investigación tipo cuantitativa, no experimental, correlacional y descriptiva. Se evaluó la adecuación del modelo y su capacidad predictiva mediante la verificación de los diferentes criterios de bondad de ajuste. Los resultados mostraron que ARIMA (1,1,0) fue el modelo más adecuado una vez que capturó el comportamiento de la serie temporal actual. Con base en los valores pronosticados se espera un aumento de 5,47% en la producción de mora para el período 2021-2023 lo que mejorará los ingresos de los agricultores y contribuirá, así a la reducción de la pobreza en el campo.

Palabras clave: Capacidad predictiva; análisis univariado; modelado de datos; producción.

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INTRODUCTION

The Andean blackberry (*Rubus glaucus*) also known as “Mora de Castilla” is native to the tropical highlands of America, cultivated from the northern regions of the Andes to the southern highlands of Mexico (Franco & Giraldo, 1998). It is considered of great economic importance as blackberry fruits are used as raw material for processed products such as juices and jams and for consumption in the fresh state (Restrepo, Luna, & Castaño-Quintero, 2019)

In Colombia, it is grown at altitudes between 1.800 and 2.300 meters above sea level, in eighteen departments of which Santander, Cundinamarca, Nariño and Huila are the most relevant producers with 60% of national production (Agronet, 2022). Moreover, it is a vital source of income for small- and medium size farmers (Cárdenas et al., 2018; Cancino, Cancino-Escalante & Cancino-Ricketts, 2020) and has in the last decade created over 51 thousand jobs, of which 39.000 are employed directly and 12,000 indirectly (Ministerio de Agricultura & Desarrollo Rural, 2021).

In view of the above, production instability affects farmers’ economic profitability therefore, it is essential to have thorough knowledge about the future development of blackberry production. In this manner, forecasting plays an important role not only in monitoring production but also in farmers´ planting decision and resource allocation (Khan et al., 2020). In fact, it can provide ground for policy makers to understand the early signs of short- and long-term changes and trend variations.

In this regard, there are a number of mathematical and statistical approaches available to help understand the dynamics of forecasting. These include the exponential smoothing approach; the single and simultaneous-equation regression methodologies; the Box Jenkins Autoregressive Integrated Moving Average (ARIMA) and the vector autoregression (VAR) models. Essentially, they are employed in different economic activities, including production, financial management, fiscal and monetary policies as well as in budgeting (Gujarati, 2010).

Despite their widespread application, each one has unique benefits and restrictions. When using data with cyclical or seasonal variations, for instance, the exponential smoothing strategy does not provide reliable forecasts, nonetheless it is very simple to use (Iqbal, 2020). The single and simultaneous-equation processes also have a number of restrictions, including the requirement to distinguish between the types of forecasting that can be produced (ex-ante and ex-post), and the fact that they can only be employed with at least two continuous variables (exogenous and endogenous) (Iqbal, 2020). Similar to this, the VAR technique also requires that data from many economic time series be incorporated into the forecasting procedure, and in some situations, this can lead to over-specified models (Brandt and Bessler, 1984); however, its advantage is that it can be estimated using ordinary least square, which is typically straightforward.

Therefore, due to the limitations of the previously mentioned methods the ARIMA approach is considered to be a viable alternative for modeling and forecasting as it is not only suitable for short-term time series, but it also increases the prediction accuracy whilst using a small number of parameters (Khan & Khan, 2020). In addition, when compared to other methodologies it is less sensitive to data fluctuations. However, one of its major disadvantages is that, unlike the exponential smoothing model, when new data becomes available the forecasting procedure has to be repeated, especially the diagnostic checking stage (Khan & Khan, 2020). Furthermore, there are a certain amount of subjective input at the different stages of the modeling process which makes it somewhat more than an art than a science (Sánchez-López et al., 2013).

In essence it is a commonly used forecasting method and it assumes a linear dependence between the times series data (Sánchez-López et al., 2013), in which it is expressed in terms of its past values as well as the current and lagged values of a “white noise” error term (Meyler, Kenny & Quinn, 1998). It involves different steps of the modeling process: identification, parameter estimation, validation and forecasting; and the iteration of these stages is crucial in identifying the most adequate model (Chen, 2008). Although it is a theory free approach, it has proven to be more accurate for forecasting real world situation when compared to other regression and econometric methods (Afzal, Rehman & Butt, 2002). In this manner, the purpose of the current study is to model and forecast blackberry production in Colombia using a Box Jenkins ARIMA approach.

The present paper is structured as follows. After this introduction, the literature review is presented followed by the methodological approach, which includes model specification, data, variables and performed tests. The third section includes the empirical results whilst the last two sections discuss and summarizes the major findings.

LITERATURE REVIEW

Even though there are many studies on the biological and agricultural aspects of blackberry production, forecast analysis has received very little attention in the literature, most probably because in many countries the data on the quantity of production is inaccurate or lacking (Cancino, Cancino-Escalante & Cancino-Ricketts, 2021). Nonetheless, this methodology has been widely employed in other fruit crops to forecast production, consumption, imports and exports.

The most similar works to blackberry production forecast are those of Khan et al. (2020) whom using time series data over the period 1997-2015 employed a Box Jenkins approach to predict guava area and production in Pakistan. The study found that the projected area was static and that production showed an upward trend with an average 2.12% increase for the period 2015-2030. Moreover, Ullah, Khan & Zheng (2018) forecasted peach area and production in Pakistan for the period 1997-98 to 2014-15 by also applying the Box Jenkins ARIMA methodology. The best model’s predictability power, performance and quality were, according to the authors, measured based on error value of the root, mean square error, mean absolute error and mean absolute prediction error. The findings of their study determined that the ARIMA model is an efficient tool and that in the short run both peach area and production showed a declining trend, due probably to high input costs, lack of cold storages and government attention to the crop.

In this same context, Hamjah (2014) forecasted the production of major fruit crops in Bangladesh using ARIMA model. Furthermore, Akın et al. (2021) employed the same method to forecast the growth trends of cherry production in Turkey, whilst Jam et al. (2013) and Burhan & Khalid (2006) predicted mango and kinnow production in Pakistan, using the same approach.

METHODOLOGY

A quantitative, non-experimental, correlational and descriptive research design was selected in order to address the purpose of the study. Respective time series data on annual production (PROD) in tons for the 1999-2020 period was obtained from Colombia´s Ministry of Agricultural and Rural Development and the Food and Agriculture Organization of the United Nations (FAO) database. In addition, a Box-Jenkins methodology using an Autoregressive Integrated Moving Average (ARIMA) model was applied to describe and forecast the yearly behavior of the proposed time series. The estimation and analysis were performed employing the E-views®9 software.

ARIMA model identification and estimation

In order to identify the correct ARIMA model the unit root test, autocorrelation (ACF) and partial autocorrelation (PACF) functions, as well as the selection criteria, are the primarily tools. In this manner, the general ARIMA (p, d, q), where the p and q parameters denote the autoregressive (AR) and moving average (MA) order and d the degree of differencing, can be written as (Judge et al., 1988):

$$\varphi\ (B)\nabla^{d}\ X_t = \ \theta\ (B)\ U_t$$

Where:

$\varphi\ (B)$ = represents the autoregressive term of order ´p´ and B is the back-shift operator

$B = \ B^m X_t = \ X_t - M \quad (m = 0{,}1{,}2 \ldots \ldots p)$

$\nabla^d\ X_t$ = is the back-shift difference operator defined as

$\nabla = \nabla\ X_t = \ (X_t - \ X_{t-1}) = (1 - B)\ X_t$

$\theta\ (B) =$ refers to the moving average term of order ´q defined as

$\theta\ (B) = 1 - \ \theta_1 B^1 - \ \theta_2 B^2 - \cdots\ \theta_q B^q$

U_t = is a white noise process

With the aim to determine whether differencing (d) is required, namely if the time series statistical properties (mean, variance, and covariance) do not change with time the Augmented Dickey-Fuller (ADF) (1979) and the Phillips– Perron (PP) (1988) stationary tests were employed. Thus, both method tests the null hypothesis that a time series is integrated of order one I (1), specifically, if it presents a unit root (non-stationary) against the alternative that it is stationary. The ACF and PACF functions were also employed to help determine the order of the AR and/or MA terms; whereas the Akaike Information Criterion (AIC) was used to choose which model was the best fit for the time series data. Finally, after the p, d and q values were determined the coefficients were estimated.

Model validation and forecast error evaluation

Diagnostic checking is a key aspect for verifying the model´s goodness of fit and its forecasting ability. Therefore, the residuals were tested for white noise (normal error, independent, zero mean and constant variance) by employing the Ljung-Box Q statistics tests. The stationarity condition of the ARIMA model was also analyzed using the inverse roots of characteristic AR polynomial.

In addition, the ARIMA forecast predictive capacity, that is, the degree to which the predicted result matches with the actual result was also evaluated. Thus, different accuracy metrics to evaluate forecast errors as proposed by Brooks (2008), particularly Theil's inequality coefficient, the mean absolute percentage error and the bias proportion, were employed. Generally, the smaller the criteria, the smaller the error size

RESULTS

The first step was to examine the time plot of the blackberry production data and to identify whether or not it could be the outcome of a stationary process. From a visual inspection of the graph of the given observations (Figure 1), it can be noted that the time series showed an upward trend, with a slight decrease during the period 2010-2011 due probably to the impact of weather changes associated with La Niña that caused a reduction in blackberry production. Notwithstanding, the presence of an upward trend suggests that the times series are non-stationary in level.

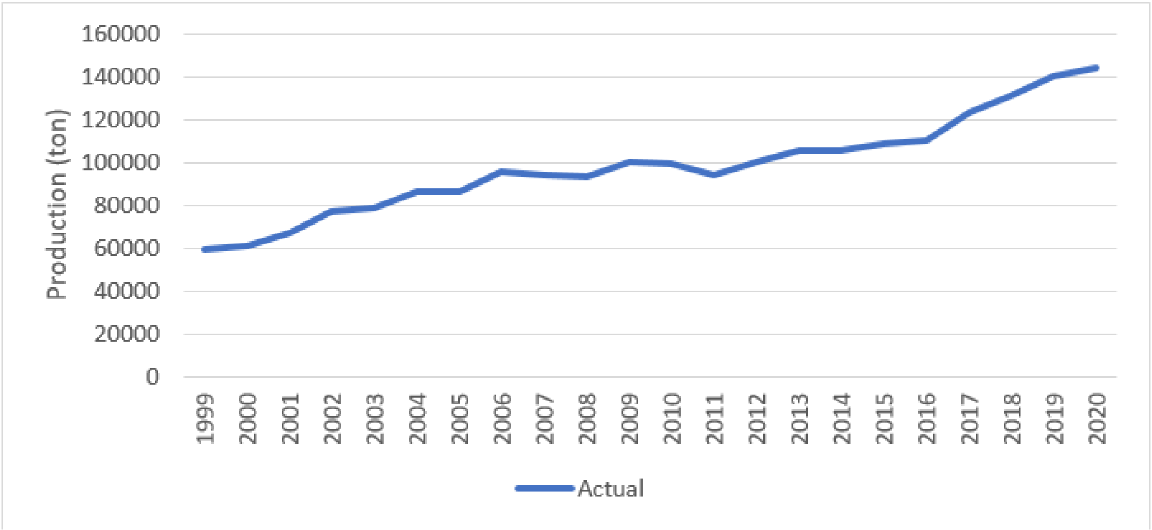


Figure 1. Blackberry production (ton) 1999-2020
Source: Own elaboration

In this manner, the non-stationarity of the times series was also confirmed with the ADF and PP tests (Table 1) that showed that for both constant and constant and trend the t-statistic values were greater than the critical value of the significance level of 0.05. However, at first difference the null hypothesis of the unit root was rejected which can be concluded the data is stationary of order one I (I).

TABLE 1.

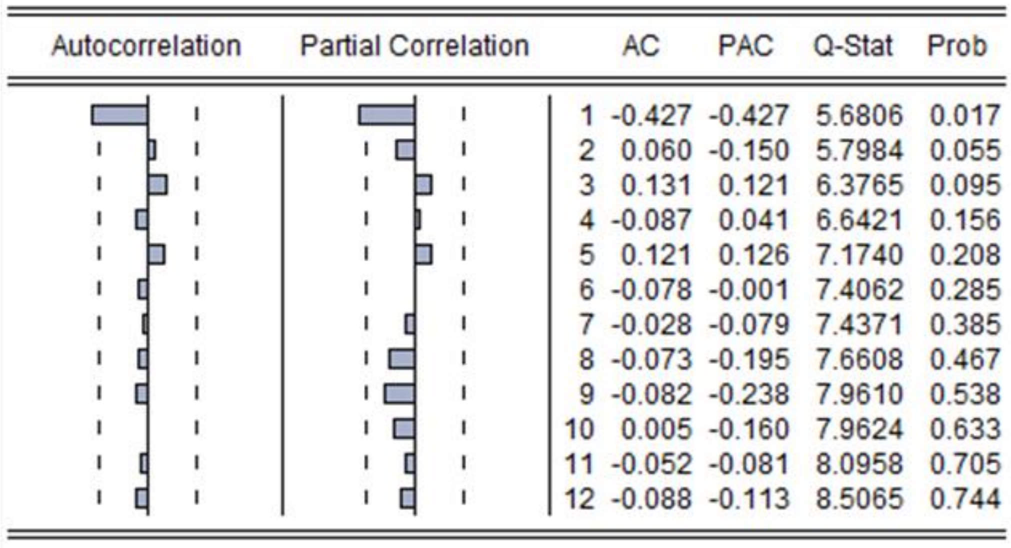
Unit root test results (ADF and PP)

Test	Variable	Level					First difference				
			t-statistics	Critical values				t-statistics	Critical values		
ADF	PROD			1%	5%	10%			1%	5%	10%
		Constant	-0.06	-3.80	-3.02	-2.65	Constant	-6.82	-3.80	-3.02	-2.65
		Constant & trend	-2.53	-4.49	-3.64	-3.26	Constant & trend	-6.66	-4.49	-3.65	-3.26
			t-statistics	Critical values				t-statistics	Critical values		
PP	PROD			1%	5%	10%			1%	5%	10%
		Constant	0.02	-3.78	-3.01	-2.64	Constant	-6.92	-3.80	-3.02	-2.65
		Constant & trend	-2.44	-4.46	-3.64	-3.26	Constant & trend	-6.89	-4.49	-3.65	-3.26

Source: own elaboration using E-views®9 (2016)

Model identification and estimation

Having determined the degree of differencing the AR and MA orders were selected by examining the ACF and PACF samples. As shown in Figure 2 the first order differenced time series of blackberry production exceeds the significance limit at lag 1 for both ACF and PACF, followed by a significant fall, hence p = 1 and q = 1 were tentatively considered.



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.427	-0.427	5.6806	0.017
		2	0.060	-0.150	5.7984	0.055
		3	0.131	0.121	6.3765	0.095
		4	-0.087	0.041	6.6421	0.156
		5	0.121	0.126	7.1740	0.208
		6	-0.078	-0.001	7.4062	0.285
		7	-0.028	-0.079	7.4371	0.385
		8	-0.073	-0.195	7.6608	0.467
		9	-0.082	-0.238	7.9610	0.538
		10	0.005	-0.160	7.9624	0.633
		11	-0.052	-0.081	8.0958	0.705
		12	-0.088	-0.113	8.5065	0.744

Figure 2. Autocorrelation and partial autocorrelation function of the PROD series.

Source: Own elaboration using E-views®9 (2016)

However, due to the subjective nature of the ARIMA methodology in order to identify the best model that fits the data a larger range of p and q values was also examined as shown in Tables 2, 3 and 4. Thus, after analyzing the AIC values in conjunction with the coefficients and statistics the ARIMA (1, 1, 0) model was chosen as it provided a more adequate representation of the available data.

TABLE 2.

ARIMA (1, 1, 0) model

Dependent Variable: PROD
Convergence achieved after 21 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	3984.707	1353.509	2.943982	0.0087
AR (1)	-0.430253	0.184401	-2.333248	0.0314
SIGMASQ	47311951	15921530	2.971571	0.0082

R-squared	0.198720	Mean dependent var	4017.476
Adjusted R-squared	0.109689	S.D. dependent var	7873.865
S.E. of regression	7429.487	Akaike info criterion	20.80561
Sum squared resid	9.94E+08	Schwarz criterion	20.95483
Log likelihood	-215.4589	Hannan-Quinn criter.	20.83800
F-statistic	3.882032	Durbin-Watson stat	2.016132
Prob(F-statistic)	0.056163		

Source: Own elaboration using E-views®9 (2016)

TABLE 3.

ARIMA (0, 1, 1) model

Dependent Variable: PROD
Convergence achieved after 9 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	3899.240	1180.419	3.303267	0.0040
MA (1)	-0.423645	0.327676	-1.292877	0.2124
SIGMASQ	47510440	16876760	2.815140	0.0115
R-squared	0.195359	Mean dependent var	4017.476	
Adjusted R-squared	0.105954	S.D. dependent var	7873.865	
S.E. of regression	7445.055	Akaike info criterion	20.81947	
Sum squared resid	9.98E+08	Schwarz criterion	20.96869	
Log likelihood	-215.4994	Hannan-Quinn criter.	20.84185	
F-statistic	2.185107	Durbin-Watson stat	2.123406	
Prob(F-statistic)	0.141391			

Source: Own elaboration using E-views®9 (2016)

TABLE 4.

ARIMA (1, 1, 1) model

Dependent Variable: PROD
Convergence achieved after 26 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	3955.169	1285.786	3.076072	0.0068
AR (1)	-0.266144	0.877048	-0.303454	0.7652
MA (1)	-0.215644	1.069727	-0.201588	0.8426
SIGMASQ	46539825	15808277	2.944016	0.0091
R-squared	0.211797	Mean dependent var	4017.476	
Adjusted R-squared	0.072702	S.D. dependent var	7873.865	
S.E. of regression	7582.241	Akaike info criterion	20.88573	
Sum squared resid	9.77E+08	Schwarz criterion	21.08469	
Log likelihood	-215.3002	Hannan-Quinn criter.	20.92891	
F-statistic	1.522683	Durbin-Watson stat	2.086495	
Prob(F-statistic)	0.244717			

Source: Own elaboration using E-views®9 (2016)

Model validation and forecast error evaluation

The appropriateness of the model was also assessed by verifying the different goodness-of-fit criteria. As can be seen in Figure 3, the proposed ARIMA model (1, 1, 0) confirms the non-existence of autocorrelation of the residuals, given that all the lags' coefficients are within the significance bands. Moreover, the Q-statistics and the p-values results presented in the last two columns corroborate that the residuals are white noise, that is, the time series is independent with zero mean and constant variance.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.086	-0.086	0.1799	
		2	-0.069	-0.077	0.3016	0.583
		3	0.150	0.138	0.9032	0.637
		4	-0.026	-0.006	0.9222	0.820
		5	0.078	0.098	1.1050	0.893
		6	-0.073	-0.086	1.2775	0.937
		7	-0.164	-0.167	2.2008	0.900
		8	-0.196	-0.280	3.6254	0.822
		9	-0.147	-0.228	4.5002	0.809
		10	-0.111	-0.197	5.0431	0.831
		11	0.076	0.097	5.3251	0.868
		12	-0.062	0.036	5.5322	0.903

Figure 3. ACF and PACF Residual

Source: Own elaboration using E-views®9 (2016)

In addition, the estimated ARIMA structure was examined in order to confirm its stability. As outlined in Figure 4 the inverse AR root lies inside the unit circle, which therefore can be concluded that the model is dynamically stable, thus the results suggest that the ARIMA model (1,1,0) is efficient to accurately forecast blackberry production.

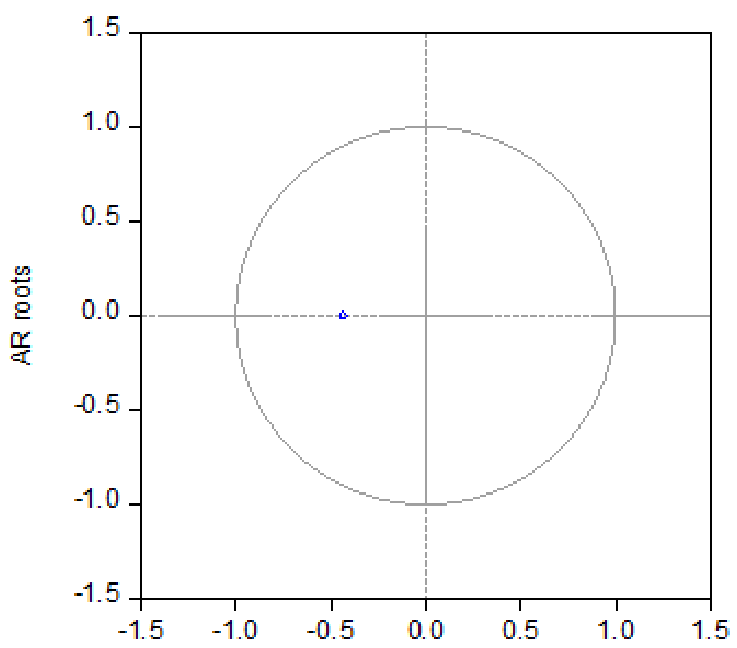


Figure 4. Inverse roots of the AR polynomial

Source: Own elaboration using E-views®9 (2016)

As a result, the model´s accuracy was confirmed when analyzing the predicted (forecast) blackberry production values against the actual trend as shown in Figure 5. The forecast curve, in general terms, captures the behavior of the actual time series, except for the period 2010-2011 when, as previously mentioned, production suffered a significant decrease due to climate changes. It also shows a better fit when compared to the other proposed models as the mean absolute percentage error (7.7%) presented a small variation between the actual and predicted series, as the error was less than 10 per cent. Moreover, Theil´s inequality coefficient (0.04) was close to zero, which indicates that the estimated results are better than the observed values. As for the bias proportion (0.05), which measures the systematic error of the forecast, that is the difference between the actual and forecasted series, was very negligible.

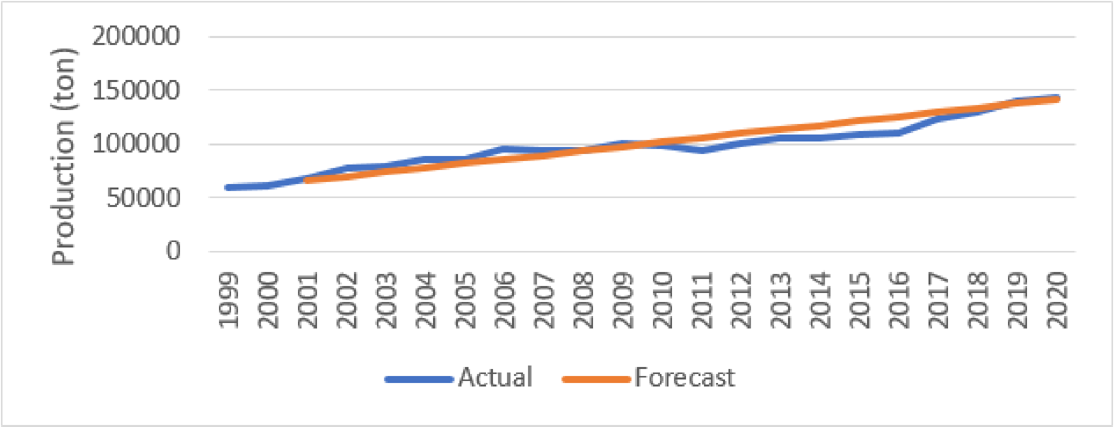


Figure 5. Actual and forecast of blackberry production (1999-2020)

Source: Own elaboration

Data forecasting

Having satisfied the model´s performance the next step was to forecast blackberry production values for the following 3 years (2021-2023). As can be seen in table 5 it is estimated that production should increase from 145.535 tons to 153.504 tons, that is, a 5.47% growth. It is however important to emphasize that blackberry production for the year 2021 has not yet been officially announced when writing this article that is why it was included in the forecast.

TABLE 5.

Forecasting blackberry production for the 2021-2023 period

Year	2021	2022	2023
Forecast (ton)	145.535	149.519	153.504

Source: Own elaboration using E-views®9 (2016)

Therefore, the results obtained in the present study are similar to those of Khan et al. (2020) in guava; Hamjah (2014) in major future crops; Jam et al. (2013) and Burhan & Khalid (2006) in mango; Ullah, Khan & Zheng (2018) in peach. In the sense that the use of ARIMA models are a viable alternative and an efficient tool for predicting the magnitude of any variable

DISCUSSION

Agriculture plays a vital role in Colombia´s economy as it contributes to the nation´s gross domestic profit, employment and farmers' social well-being (Cárdenas et al., 2018; Arguello & Valderrama-Gonzalez, 2015; Henley, 2012). However, the uncertainty of agricultural production makes investment and planting decisions difficult therefore, forecasting production provides farmers with information that will allow them to become more efficient and allocate resources optimally. Thus, the Box Jenkins ARIMA methodology is an important tool in forecasting blackberry production in Colombia.

Likewise, in addition to contributing to the knowledge of blackberry production in Colombia, the ARIMA model has many other strengths. First, it is appropriate for any time series data, and second, there is no need for the forecaster to choose a prior value of any parameter (Gajbihe, Wankhade & Mahalle, 2010). Moreover, the structural approach of the ARIMA technique is to build candidate models, remove incorrect ones, and thus use the most suitable model. This methodology prevents the choice of a particular model that may not be the most appropriate one (Majid & Mir, 2018).

Furthermore, it can be argued that within the structure of univariate time series-modeling studies, the ARIMA approach is also a significant tool for formulating agricultural policies (Khan et al., 2020). Therefore, it is quite essential to have a clear understanding of the present as well as forecasting the future when aiming to ensure farmers´ income and improve crop production productivity.

CONCLUSIONS

In this manner, the present study used historical yearly blackberry production (1999-2020) to forecast future production (2021-2023) by employing a Box Jenkins ARIMA approach. The predictability power of the developed model was assessed by comparing the actual and the simulated values and the results revealed that the selected model (1, 1, 0) showed a high accuracy and ability to simulate the dynamic behavior of blackberry production in Colombia. As such, the projected blackberry production in Colombia is quite favorable as it is expected a 5.47% growth for the following three years. This will improve farmers´ income and thus contribute to the reduction in poverty.

There is no doubt that the research findings are important as it is not only a useful tool to forecast blackberry production, but it also provides policy makers and farmers to valuable information on planning and planting decisions as well as resource allocation. Nonetheless, it is recommended that for future studies a larger data set should be included in order to provide higher accuracy level.

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