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Forecasting tourism arrival in Panama using ARIMA models*

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Abstract

The tourism industry stands out as a significant source of revenue. Beyond driving economic growth and job creation, tourism also plays a key role in stimulating infrastructures development and promoting services tourist. This study aimed to forecast tourist arrivals in Panama using ARIMA models. Monthly data on tourist arrivals to Panama were collected. The results show that the ARIMA model provides reasonable and useful forecasts for tourist arrivals in Panama, with an acceptable level of accuracy. Therefore, in conclusion, the results of this study become significant for the strategic planning of tourism in Panama, in response to the dynamics of this important sector of the national economy.

Keywords: Tourism; times series; forecast; Box-Jenkins model; ARIMA.

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Pronóstico de la llegada de turistas a Panamá utilizando modelos ARIMA

Resumen

La industria del turismo se destaca como una fuente significativa de ingresos. Más allá de impulsar el crecimiento económico y la creación de empleo, el turismo también juega un papel clave en el estímulo al desarrollo de infraestructuras y la promoción de servicios turísticos. Este estudio tuvo como objetivo pronosticar la llegada de turistas a Panamá utilizando modelos ARIMA. Se recopilaron datos mensuales sobre la llegada de turistas a Panamá. Los resultados muestran que el modelo ARIMA proporciona pronósticos razonables y útiles para la llegada de turistas a Panamá, con un nivel aceptable de precisión. Por lo tanto, en conclusión, los resultados de este estudio se vuelven significativos para la planificación estratégica del turismo en Panamá, en respuesta a la dinámica de este importante sector de la economía nacional.

Palabras clave: Turismo; series temporales; pronóstico; modelo Box-Jenkins; ARIMA.

Introduction

The forecast of tourism demand has been a topic of interest in specialized research since the late 1990s. In the bibliometric study conducted by Liu et al. (2018), 543 papers published in the Web of Science (WOS) since 1972 were identified, although growth did not occur until 2006. One of the topics that has attracted the most attention is predicting tourist behavior through econometric models, artificial intelligence approaches, or time series (Zhang et al., 2020; Naranjo & Martínez, 2022).

Regarding the latter, and specifically Autoregressive Integrated Moving Average (ARIMA) models, they are widely used to predict tourism behavior (Zhou et al., 2022), and numerous authors have demonstrated their predictive power (Athanasopoulos et al., 2011). One advantage of these models is their ability to provide short-term predictions due to their capacity to capture dynamics in the behavior of the studied variable (Song et al., 2019). Their widespread use highlights their validity and usefulness in predicting tourism dynamics.

In line with the above, Du Preez & Witt (2003) state the advantage of ARIMA over univariate and multivariate state space modeling for forecasting arrivals to Seychelles. Similarly, Kim et al. (2011) analyzed various time series models for tourism prediction and found that SARIMA produced accurate point predictions and narrow prediction intervals. Also, Gunter & Önder (2015) concluded that univariate ARIMA (1,1) models were the most accurate in predicting tourist arrivals to Paris from the United States and the United Kingdom. Jayasundara (2019) corroborated the predictive power of ARIMA models for forecasting tourism demand in Sri Lanka. Recently, Wong et al. (2007) asserted that ARIMA models offer the advantage of being adjustable to capture specific seasonal patterns of each region or country.

Traditionally, research on tourism demand has focused on countries such as the USA, England, Spain, Australia, and China, primarily (Liu et al., 2018; Sun et al., 2019; Li et al., 2020; Zhang et al., 2020). However, nowadays, it is possible to find studies focused on other less studied destinations such as Croatia (Baldigara & Mamula, 2012), Thailand (Janjua et al., 2021), Armenia (Tovmasyan, 2023), among others. However, no studies have been found that analyze the prediction of tourism demand in Panama, despite it being a sector of enormous economic importance for the country.

Due to the need to consider the particularities of the tourism industry in different contexts (Song & Witt, 2000), the application of time series analysis, particularly the ARIMA model, is of great importance for predicting tourism behavior in Panama. By employing ARIMA techniques, the effectiveness of public policies and marketing campaigns can be evaluated, and informed projections about future trends can be made (Hyndman & Athanasopoulos, 2018; Ospina et al., 2023).

The objective of this work is, therefore, to estimate tourist arrivals to Panama using ARIMA. By shedding light on the complexities of tourist arrivals, this study aims to inform strategic planning efforts and foster the continued prosperity of Panama's tourism sector in the years to come.

1. Theoretical foundation

It is commonly accepted that the tourism industry is key to the growth of economies (Nissan et al., 2011; Nugra et al., 2021; Anzaldúa-Soulé et al., 2021), due to its impact on job creation (Varzakas & Metaxas, 2024), the circulation of money within communities (Silva & Roque, 2024), economic diversification, infrastructure development (Adeola et al., 2018), and social benefits (Loor et al., 2021), among other aspects. According to the World Tourism Organization (WTO) (World Trade Organization, 2023), the tourism industry contributes to 7.6% of the global GDP, which translates to 7.7 trillion US dollars. This year, there was a 22% increase compared to the previous year, and it is only at 23% of reaching pre-pandemic figures. In 2022, the total new employment generated was 22 million, which represents an increase of 7.9% compared to the previous year. This translates to 1 in every 12 jobs generated belonging to this sector.

Similarly, the tourism industry creates employment indirectly. According to the WTO (World Trade Organization, 2023), for every job generated in the sector, approximately one and a half additional (indirect) jobs are created in other productive activities related to tourism. Additionally, it is estimated that three workers indirectly depend on each person working in hotels, such as travel agency personnel, guides, taxi and bus drivers, food and beverage suppliers, laundry workers, textile workers, gardeners, souvenir shop staff, and others, as well as airport employees.

During the year 2022, international traveler arrivals reached the figure of 969 million, which doubled that of 2021 (102%) (World Trade Organization, 2022). The United States was the country with the highest international tourism earnings in 2022. That year, international tourism receipts in the United States amounted to approximately 135 billion US dollars. While this figure marked a strong increase compared to the first two years of the coronavirus (COVID-19) pandemic, it remained below pre-pandemic levels. Meanwhile, Spain and the United Kingdom followed in the ranking in 2022, with around 73 billion and 68 billion US dollars, respectively.

Panama is primarily a service-based economy. Within this sector, tourism plays a significant role. Tourism in Panama generated 4,720.6 million balboas in revenue in 2022, representing a 105.1% increase compared to the previous year, based on official statistics from the General Comptroller of the Republic. The World Travel & Tourism Council (WTTC, 2023) indicated, through its Annual Economic Impact Report (EIR), that in 2022, tourism contributed $11 billion to the Panamanian economy, 0.9% higher than the 2019 figure, and accounting for nearly 16% of the isthmus economy's GDP.

In 2022, the contribution of Panama's Travel and Tourism sector to the GDP grew by 78.3% compared to the previous year, reaching $11 billion, which accounted for 15.8% of the Panamanian economy, surpassing the figures reported in 2019 when the sector represented 15.6% of the national GDP. Last year, the sector generated 325.2 thousand jobs, accounting for 17% of total employment in the country, just 2.5% below 2019 levels. It is worth noting that, during the past year, the arrival of international travelers increased, generating an expenditure of nearly $7.6 billion, marking a 103.4% growth compared to 2021. Meanwhile, domestic travelers accounted for over $1.9 billion, a 30.3% increase from 2021 figures, and surpassing by 5% what was reported in 2019.

> Julia Simpson, President and CEO of WTTC stated: Panama's Travel and Tourism sector is rebounding, demonstrating a strong preference from travelers worldwide to visit and explore all that the country has to offer.
> Over the next 10 years, the sector will generate nearly 113 thousand new jobs in Panama, representing one in every five jobs in the country. (World Travel and Tourism Council, 2023, párr. 11-12)

Likewise, by the end of 2023, it is projected that the tourism sector will surpass 2019 employment levels by 1.7%, reaching nearly 400 thousand jobs generated in Panama, representing 17% of total employment in the country (WTTC, 2023). According to the EIR, it is estimated that by the end of 2023, Panama's tourism sector will account for 16.4% of its total economy. Overall, the demand for tourism in Panama has shown sustained growth. However, this market has experienced various fluctuations due to the volatility of certain factors and external interventions, such as those caused by the pandemic.

One fundamental aspect of managing a tourism company is to know what the level of demand will be for the upcoming periods. Short-term predictions provided by time series analysis serve as an excellent complement to available statistical information, which is often obtained with a delay, preventing the company from analyzing the sector and making decisions until that information is available. On the other hand, prediction also provides valuable information for designing public policies by enabling the planning of employment programs and investments in infrastructure, among other aspects.

2. Methodology

Most studies on forecasting tourism demand have paid more attention to the flow of international tourists due to the availability of statistical data (Song et al., 2019). To obtain information on tourism demand, the monthly number of visitors entering through Tocumen International Airport, the country's main airport, was obtained for the period from January 2012 to December 2022. The data were requested from the Panama Tourism Authority (Autoridad de Turismo de Panamá, 2023), the public institution responsible for developing, promoting, and regulating the tourism industry in Panama.

The Panamanian government announced the first case of COVID-19 on March 9, 2020, and on March 22 of that same month, Tocumen International Airport was closed to international flight arrivals and departures. Midway through October 2020, the air border was gradually reopened for some countries. Therefore, during that time, there were no available data on tourist arrivals.

According to Kaya & Turkoglu (2021), the absence of data is addressed through different methodologies, depending on the data structure. With the advent of Big Data, imputation techniques based on neural networks (Cao et al., 2018; Park et al., 2023) have notably attracted attention; however, Denk & Weber (2011) emphasize that a basic strategy for addressing the problem of missing data in a time series is to use the last known observation to fill in the time series or calculate the arithmetic mean to assign values to the missing data. Indeed, several univariate imputation methods (Moritz et al., 2015; Phan et al., 2020) are used as simpler forms of imputation, reconstructing missing values of a single variable based on its temporal dependence. In this regard, in this work, estimates of missing data have been made by calculating the historical monthly mean of the series.

2.1. ARIMA Models

The Autoregressive Integrated Moving Average model, known as ARIMA (Box et al., 2015), is a widely recognized statistical model for forecasting univariate time series, combining three techniques: Autoregression (AR), Integrated (I) Differencing, and Moving Average (MA). Autoregression explores the relationship between the variable and its lagged values; stationarity differencing seeks to eliminate trends or seasonal patterns by calculating differences between successive observations, while moving average utilizes past forecast errors to project future values. The general form of the ARIMA model is described in terms of the parameters p, d, q, which define the order of the autoregressive component, the degree of differencing, and the order of the moving average component, respectively. Hence, the notation ARIMA (p, d, q).

The main idea of the ARIMA model is to transform a time series into a stationary one and thus turn it into a purely random process to properly fit a forecasting model (Box & Jenkins, 1976; Peña, 2010). The mathematical formulation of the ARIMA model is presented as follows.

$$y_t - y_{t-1} = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \cdots - \theta_q a_{t-q}$$

Were, p represents the autoregressive order; d represents the degree of differencing; q represents the order of the moving average; y_t represents the time series data at time t; t is an error term; $\phi 1 \dots \phi p$ are autoregressive coefficients; and $\theta 1 \dots \theta q$ are moving average coefficients.

2.2. Box-Jenkins Methodology

The Box-Jenkins methodology (Box & Jenkins, 1976) is a tool that involves defining a mathematical model to describe the behavior of a historical dataset. It assumes that the time series to be predicted is generated by a variety of stochastic processes. The process requires a monthly or quarterly series with a significant number of observations.

The central idea of the Box-Jenkins methodology is to provide a set of procedures for selecting the most appropriate model among Autoregressive (AR), Integrated Autoregressive Moving Average (ARIMA), and Seasonal Autoregressive Integrated Moving Average (Seasonal SARIMA) models that fits the data of an original time series and thus make forecasts and comparisons between actual and estimated data.

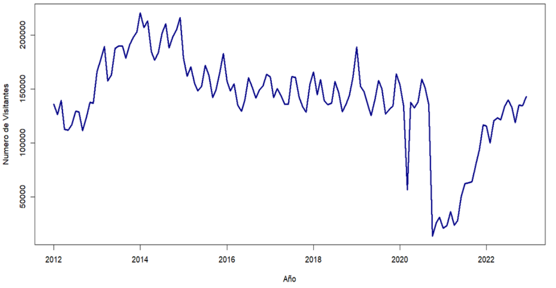
In general, to build a time series model through the Box-Jenkins methodology, four phases are developed: 1) Stage of model identification and selection; 2) Stage of model parameter estimation; 3) Stage of validation of the selected model; and 4) Stage of prediction.

The first phase consists of identifying the model. To do this, it is necessary to check if the series is stationary; that is, if it remains constant over a specific period. This is achieved through the analysis of simple autocorrelation functions and partial autocorrelation functions. The second phase focuses on estimating the parameters of the selected model. Currently, due to technological advances, it is possible to estimate the parameters of one or more models. The third stage involves validating the proposed models, ensuring that they meet the established theoretical requirements. The final phase focuses on predicting future values.

In this work, the Box-Jenkins methodology is employed to describe the pattern of behavior of the time series of visitors entering Panama. This process involves a careful analysis of historical data and previous patterns in the time series, to develop an appropriate model and make forecasts for short-term periods.

3. Results and discussion

The analysis of tourism activity can be evaluated considering aspects such as tourist arrivals, the number of overnight stays, hotel occupancy, average spending, length of stay, and countless other tourism variables conditioned by the tourist destination. Based on results from current literature on tourism demand at the regional level, this study adopts the number of visitors entering through Tocumen International Airport as a representative indicator of tourism demand in Panama. The variable used is the monthly number of visitors entering from January 2012 to December 2022 (see Figure I), providing 132 monthly data points for the historical series.



Source: Own elaboration, 2024.

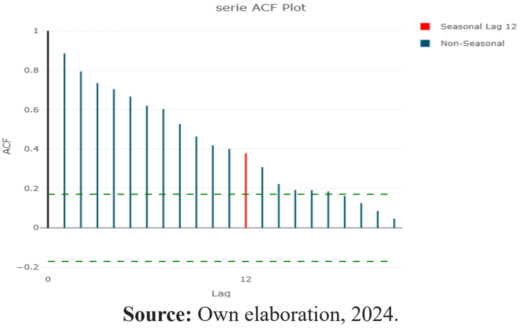
Figure I: **Time series plot of monthly visitors entering Panama through Tocumen International Airport. Years: 2012-2022**

A preliminary analysis of the series, illustrated in Figure I, shows a marked increasing trend in the number of visitors entering through Tocumen International Airport starting from the year 2012, accentuated in the period 2013-2015; then a decline is observed from 2015, and it remains somewhat unstable with irregularity around the trend until the end of 2019. Additionally, peaks and valleys are shown indicating the presence of a seasonal component within each year and repeating in the following periods. It is notable that tourist arrivals to Panama experienced a sharp drop in mid-2020, because of the global COVID-19 pandemic.

In summary, the series exhibits a trend component; provides evidence that it is not stationary in mean; also displays high irregularity around the trend, implying non-stationarity in variance; and, the seasonal component is observed, demonstrating that the series can be modeled with a Seasonal Autoregressive Integrated Moving Average (SARIMA) process.

3.1. Stage of model identification and selection

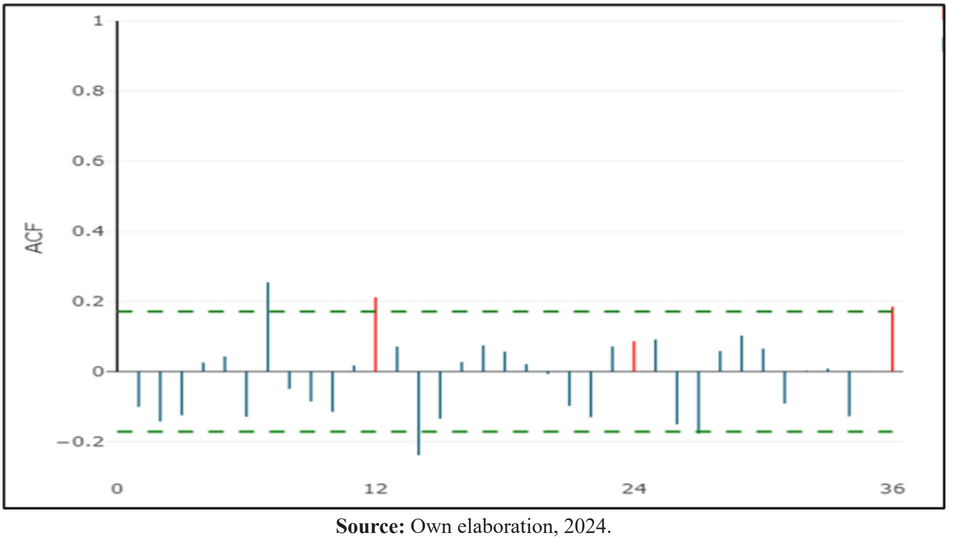
Continuing with the series decomposition and following the Box-Jenkins methodology for modeling tourism data, the stationarity of the time series is verified by checking that the mean and variance are stationary. In this case, the autocorrelation function is presented (see Figure II), followed by the augmented Dickey-Fuller test to analytically verify whether the series is stationary.



Source: Own elaboration, 2024.

Figure II: **Autocorrelation plot used to test stationarity**

Looking at Figure II, there is no evidence of a seasonal pattern per se; however, it is worth noting that the series is dominated by the trend, which could be masking this pattern. On a deterministic level, it is noticeable that the first autocorrelation approaches one, and the bars decrease slowly. This behavior is typical of non-stationary series, so it is necessary to apply some differencing to the series to eliminate seasonality and thus achieve a stationary series before applying the model. In Figure III, the series transformed with the first difference of the series is visualized.

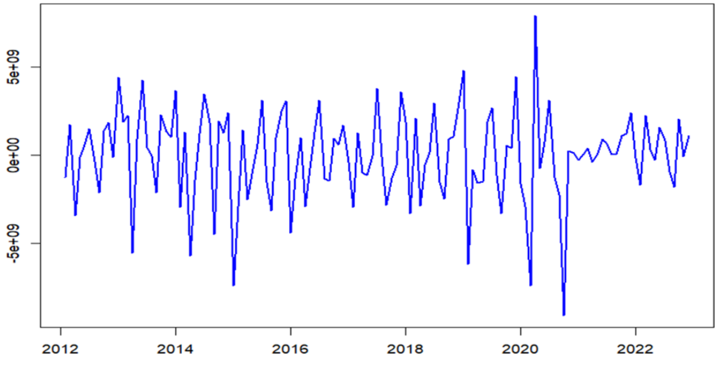


Source: Own elaboration, 2024.

Figure III: **Autocorrelation plot after first-order differencing**

When applying differencing to the series, the correlogram with 36 lags is generated (see Figure III), where it can be observed that the seasonal component is present, as it is seen at lag 12 and repeats in the following years (multiples of 12). It is concluded, therefore, that the series exhibits a seasonal pattern.

Based on the diagnosis of the series at the previously analyzed points, we proceed to work with the transformed series. Once the variance has been transformed and stabilized, differencing is performed to stabilize the series in mean and validated using the Dickey-Fuller test. To corroborate homogeneity in variance, the Levene test is used. The resulting graphical representation is shown in Figure IV.



Source: Own elaboration, 2024.

***Figure IV:* Plot of the series stationary in mean and variance**

In Figure IV, it can be observed that the series has significantly improved after the transformation, being stationary in both mean and variance. To confirm that the series is indeed stationary in mean, it is evaluated using the Dickey-Fuller test, and to validate that it is stationary in variance, it is evaluated in the first difference using the Levene test.

In the first case, the following hypotheses are proposed: Ho: The series is not stationary. H1: The series is stationary in mean. The results of the Dickey-Fuller test, after transforming the original time series with the first differencing, are shown in the following Table 1.

Table 1
Results of the Stationarity Test in Mean (unit root)

Test	t-statistic	P value
Dickey-Fuller test	-6.3374	0.01

Source: Own elaboration, 2024.

In Table 1, the Dickey-Fuller test is observed with a p-value < 0.05, indicating sufficient evidence to reject the null hypothesis of non-stationarity of the time series in first difference, during the period from January 2012 to December 2022, determining that the series is stationary in mean, with a significance level of 5%.

To validate stationarity in variance, the Levene test poses the following hypotheses: Ho: The series is constant over time. H1: The series is not constant. The results of the Levene test, after transforming the original time series with the first differencing, are shown in the following Table 2. With the results from Table 2, where the P-value is >0.05, it is shown that the series is homogeneous and that the variances over time are constant or stable.

Table 2
Results of the Stationarity in Variance Test

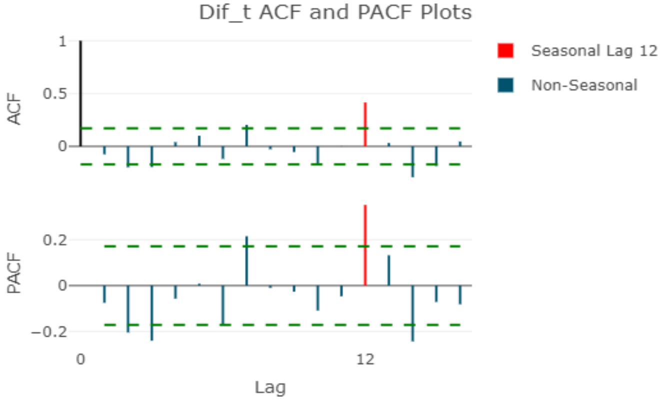
Test	MS	MS	F	P value
Homogeneity in Variance Test	57.38490	328.7861	0.2549	0.9923

Source: Own elaboration, 2024.

Based on these results confirming the stationarity in mean and variance of the visitor time series, we proceed to the estimation stage to determine which model best fits, based on the autocorrelation functions.

3.2. Estimation Stage of Model Parameters

To determine the SARIMA models (p,d,q) x (P, D, Q), it is necessary to study the graphs of the simple autocorrelation function (ACF) and the partial autocorrelation function (PACF) of the transformed and differenced series. Both graphs are presented in Figure V, and the autoregressive (p) and moving average (q) values in the regular and seasonal parts of the model are identified accordingly.



Source: Own elaboration, 2024.

Figure V: **Autocorrelation function (ACF) and partial autocorrelation function (PACF) differentiated and transformed for the monthly visitors entering Panama**

Considering the results of the simple and partial autocorrelation functions, the following models are proposed (see Table 3).

Table 3
Proposed SARIMA models

Model	Parameters	AIC	BIC
1	(0,1,0) (1,0,1)	2968.880	2977.506
2	(2,1,2) (1,0,0)	2969.773	2987.024
3	(0,1,0) (0,0,1)	2971.382	2982.883
4	(0,1,2) (1,0,0)	2970.000	2981.500
5	(0,1,0) (1,0,0)	2970.291	2976.041
6	(0,1,0) (0,0,1)	2970.745	2976.495
7	(0,1,0) (1,1,0)	2741.081	2746.640

Source: Own elaboration, 2024.

The Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) are based on the likelihood of the model; they penalize its complexity, which is measured by the number of model parameters in both cases, although in a different manner. The model with the lower value is selected. Evaluating the information in Table 3, it is observed that Model 7 presents smaller values of both AIC and BIC criteria compared to the other models, which better fits the data. Based on this criterion, the SARIMA (0,1,0) (1,1,0) model is selected.

3.3. Stage of Validation of the Selected Model

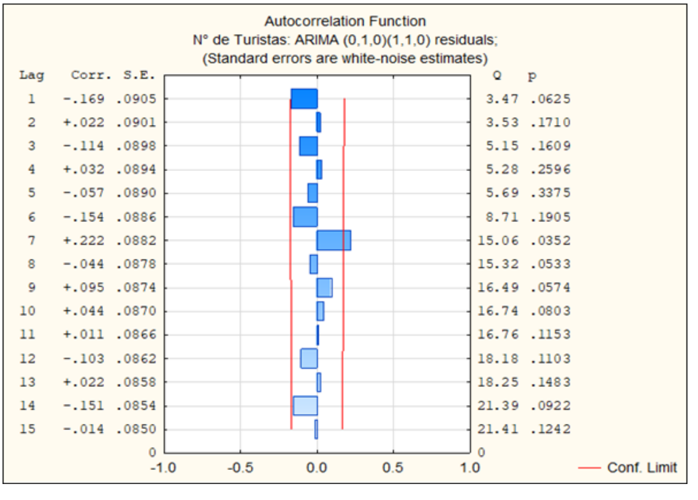
The first step in validating ARIMA/SARIMA models is to verify that the model parameters comprising the explanatory variables meet statistical significance. From the results presented in Table 4, it can be deduced that the coefficient Sar1 is significant at a 5% significance level.

Table 4
Parameters of the SARIMA model (0,1,0) (1,1,0)

	Coefficients	Standard Error	Z Value	Pr
Sar1	-0.40023	0.0789	-5.099	0.000

Source: Own elaboration, 2024.

To ensure the validity and suitability of the model and the effectiveness of predictions, the residuals of the estimated model should exhibit white noise behavior; that is, they should be normally distributed, with zero mean and covariance, and constant variance. The structure of white noise can be analyzed through the correlogram of the residuals (see Figure VI).

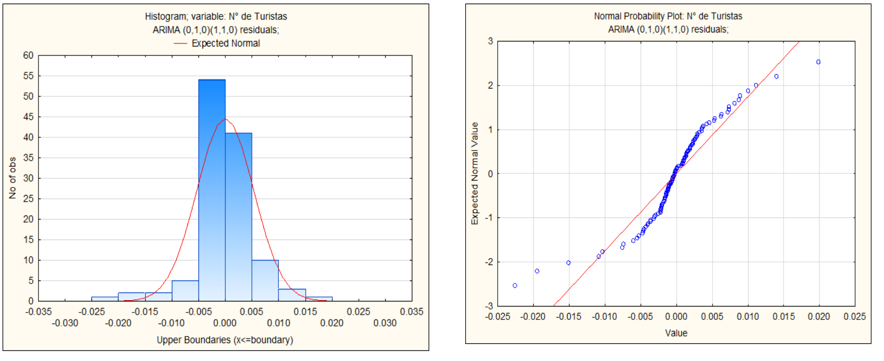


Source: Own elaboration, 2024.

Figure VI: **Autocorrelation function (ACF) of model residuals and white noise (red lines) at 95% confidence level**

In Figure VI, it can be observed that the lags fall within the confidence bands; hence, it can be affirmed that the residuals exhibit a white noise structure. In summary, the series residuals are entirely random and do not show any dependence among them.

To verify the normality of the residuals of the proposed SARIMA (0,1,0) (1,1,0) model, the histogram and the probability plot are shown (see Figure VII). Upon observing the histogram of the residuals, the model fits the data as it exhibits symmetry around zero; therefore, the residuals are random. The normal probability plot of the residuals shows that they follow a straight line, indicating they are normally distributed with few outliers.



(a) **(b)**

Source: Own elaboration, 2024.

Figure VII: **(a) Histogram and (b) Probability plot (To verify the normality of the residuals of the proposed model)**

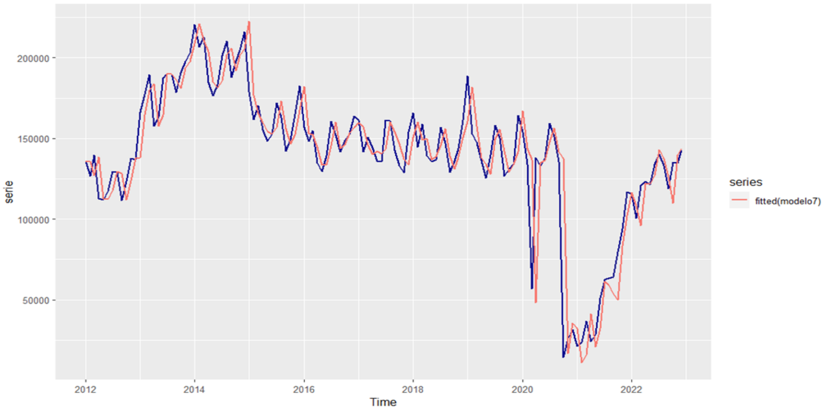
Next, in Table 5, error measures are presented as an additional element to evaluate the predictive capability of the resulting model and support its selection for forecasting the number of visitors arriving at Tocumen International Airport in Panama City.

Table 5
Accuracy Measures of SARIMA Model (0,1,0) (1,1,0)

	DAM	ECM	RECM	PEM	PEMA
SARIMA Model	32332.713	3097523787	32332.71314	0.2322	0.249401

Source: Own elaboration, 2024.

After validating the residuals of the SARIMA (0,1,0) (1,1,0) model, the next step is to forecast the number of international tourists who entered Panama City during the last six months of 2022. Figure VIII shows the graph of the original series and the values adjusted with the SARIMA model. It is observed that the forecasts closely follow the original values of the series of visitors entering the country through Tocumen International Airport.



Source: Own elaboration, 2024.

***Figure VIII:* Observed Values and Values Adjusted mean monthly visitors entering Panama using the SARIMA Model (0,1,0) (1,1,0)**

3.4. Forecasting stage

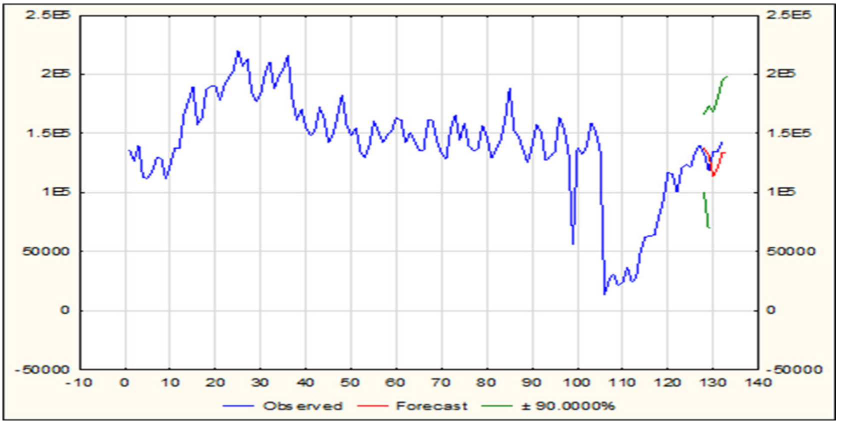
In Table 6, the forecast for international tourist demand based on the estimated model, the actual values, and the confidence intervals for the months of July 2022 to December 2022 are presented.

Table 6
Forecasting with the Model SARIMA (0,1,0) (1,1,0)

Month (2022)	Forecast	Actual Value	Lower Limit	Upper Limit
July	137,260.2	139,941	99742.97	166529.4
August	132,023.8	133,160	69681.75	173219.6
September	113,474.7	118,859	0	168158.7
October	121,252.4	135,254	0	180237.4
November	134,233.8	134,687	0	194682.1
December		142,837	0	198610.9

Source: Own elaboration, 2024.

In Figure IX, the graph of the original series and the forecasts for the period 2022-2023 with their respective confidence intervals are shown. It can be observed that these forecasts maintain the seasonal pattern and the upward trend of the series of tourists entering Panama.



Source: Own elaboration, 2024.

Figure IX: **Forecast of tourist monthly arrivals to Panama through Tocumen International Airport**

In summary, the use of ARIMA models in predicting tourism demand is important because it allows capturing and analyzing trends, seasonalities, and other patterns in the data, which is essential for sector planning (Wong et al., 2007). In this regard, knowing future trends (Law et al., 2019), sector companies can allocate their resources more efficiently, such as accommodation (Pan & Yang, 2017), transportation, and tourist services.

On the other hand, with a clear understanding of future demand trends, countries can develop and tailor tourism products and services to meet the needs and preferences of expected visitors (Hanafiah et al., 2022).

Conclusions

This work demonstrates the utility of the Box-Jenkins methodology and seasonal ARIMA (0,1,0) (1,1,0) for forecasting tourism demand in Panama, and the results show that the trend will be increasing. The use of ARIMA models to predict tourism demand is important because it allows for capturing and analyzing trends, seasonality, and other patterns in the data, which is essential for sector planning. Thus, understanding future trends allows companies in the sector to allocate their resources most efficiently, such as accommodation, transportation, and tourism services. For example, if a significant increase in demand is forecasted during certain periods, destinations can increase accommodation and transportation capacity to meet the anticipated demand.

On the other hand, by forecasting tourism demand, destinations can anticipate visitor peaks and take measures to better manage the visitor experience. For example, strategies can be implemented to reduce congestion in popular tourist spots during periods of high demand, ensuring a more satisfying experience for visitors.

Likewise, with a clear understanding of future demand trends, countries can develop and adapt tourism products and services to meet the needs and preferences of visitors. This may include creating new tourist attractions, events, or specific tour packages for identified market segments. In addition, forecasting tourism demand can also guide destination marketing strategies. For example, specific promotional campaigns can be targeted during periods of expected lower demand to stimulate visits during off-peak times.

Finally, anticipating changes in tourism demand enables destinations to better prepare for unforeseen events such as economic crises, natural disasters, or health emergencies. By considering different scenarios of future demand, destinations can develop more effective contingency plans and recovery strategies.

Taking into account the aforementioned advantages that tourism demand entails, further studies could encompass forecasting passenger arrivals by origin. This would allow for the design of specific strategies tailored to the preferences of tourists arriving in the country.

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