European Journal of Economic and Financial Research
ISSN: 2501-9430
ISSN-L: 2501-9430
Available on-line at: http://www.oapub.org/soc

DOI: 10.46827/ejefr.v8i6.1847 Volume 8 | Issue 6 | 2024

MODELING TOURIST ARRIVALS IN THE ISLAND GARDEN CITY OF SAMAL: IMPLICATIONS TO BUSINESS OPERATIONS OF TOURISM-RELATED INDUSTRY

Lemuel B. Asdang[1i],
Stilo Floyd P. Schneider[2]
[1]MBA Program,
Professional Schools,
University of Mindanao,
Philippines
[2]Faculty,
University of Mindanao,
Philippines

Abstract:
This study aimed to model the tourist arrivals in the Island Garden City of Samal (IGaCoS) by utilizing the autoregressive integrated moving average (ARIMA) method. Specifically, this paper sought to determine whether there was a statistically appropriate forecasting model using the ARIMA approach, based on which it would be possible to reasonably forecast the number of tourist arrivals in IGaCoS. Quantitative secondary data were analyzed by employing the Box-Jenkins ARIMA. The time series plot was characterized by an apparent increasing trend combined with intermittent sinusoidal oscillations. The time series revealed a steady, gradual increase up until 2020. Next, a sharp decline was observed midway through 2020, indicative of the ill effects of the COVID-19 pandemic. A gradual increase was noted once more, starting in 2021, with some fluctuations. The Augmented Dickey-Fuller (ADF) test revealed that the time series was non-stationary at level— but was made stationary after differenced twice. The ARIMA (1,2,1) model was found to be statistically significant. The fitted model initially showed some notable deviations from the original data, but, with time, converged closely to the actual values, proving it is a reliable way to represent underlying patterns. The ARIMA (1,2,1) model, selected for having the lowest AIC and BIC values and a MAPE within the acceptable range for reasonable forecasting, was used to predict tourist arrivals in IGaCoS over the next six months. The forecasted values suggested a mix of fluctuations and stability. There was a noticeable upward trajectory at the beginning, which was followed by a slight decline at the end that yet remained stable. The forecasted results from the ARIMA (1,2,1) model may provide businesses with a roadmap for comprehensive planning in terms of operational and strategic concerns. This study

[i] Correspondence: email l.asdang.521989@umindanao.edu.ph

helped address Sustainable Development Goal (SDG) No. 8, Decent Work and Economic Growth.

JEL: L83, R11, C53

Keywords: business administration, tourist arrivals, ARIMA, sustainable tourism, Philippines

1. Introduction

The inherent uncertainty and fluctuations in tourist arrivals present significant challenges which affect the operational planning and decision-making processes of tourism-related businesses (Doğan et al., 2022; Gričar, 2023; Johar et al., 2022; Makoni & Chikobvu, 2021; Nikitenko, 2024; Ruiz Reina, 2021; Williams et al., 2021). Without accurate models to predict tourist flows, businesses are vulnerable to the risk of either over-preparation, leading to increased operational costs, or under-preparation, resulting in missed opportunities and customer dissatisfaction. In other words, having accurate tourist arrival forecasts for strategic and operational decision-making activities in the tourism-related industry is paramount in this regard (Anisa et al., 2021; Diunugala & Mombeuil, 2020; Law et al., 2019).

There is no disputing that tourism is one of the major economic sectors in the world. In addition to generating jobs and promoting exports, tourism also has significant cultural, environmental, and heritage significance (Ghalehkhondabi et al., 2019; Goumas & Kontakos, 2021; Rodrı´guez & Gallego, 2020). In 2018, the tourism industry generated 5% of the direct GDP and employed almost 235 million people, according to the United Nations World Tourism Organization (UNWTO) (Wu et al., 2021). In his study, Tharu (2019) conjectured that the amount of tourist receipts has a major impact on the GDP and global economy. Accordingly, the positive relationship between tourism industry and economic development is well documented in existing literatures (Esquivas et al., 2021; Ghalehkhondabi et al., 2019; Haryanto, 2020; Juznik Rotar et al., 2019; Khan et al., 2020; Maliberan, 2019; Serrona et al., 2022).

In the Philippine economy and in the national job market, the tourism sector is deemed important (Andulana et al., 2021). It was highlighted by Santamaria (2020) that to generate investment, foreign exchange, and employment and to continue shaping and enhancing the sense of national pride for all Filipinos, tourism is deemed an "*indispensable element of the national economy and an industry of national interest and importance*," according to the Tourism Act of 2009 (RA 9593). The Philippines has become one of the world's most popular travel destinations. Given that it is rated 67th out of 184 countries, the tourism sector is one of the nation's key sources of income (Maliberan, 2019); in fact, it is the bread and butter of an emerging economy (Khan et al., 2020). Over the past 10 years, the number of tourists visiting the country has increased significantly and continuously. With 8,260,913 arrivals in 2019, they accelerated to a growth rate of 6.07%, creating 5.7 million employments in the same year (Caynila et al., 2022; Department of Tourism, 2019), and, additionally, PHP550.2 billion was earned from foreign tourist visits (PWC, 2020), contributing almost 12% to the nation's GDP in the same year (Serrona et al., 2022).

Yet, in the first quarter of 2020, almost all human endeavours came to a halt with the occurrence of the COVID-19 pandemic. Caynila et al. (2022) and Huynh et al. (2021) stressed that as nearly every nation, including the Philippines, has closed its borders and implemented tight quarantine rules to stop the spread of the virus, the tourism industry is one of the economic sectors that has been particularly hit by the pandemic hard. The surge in visitor visits caused by viruses and newly discovered illnesses is a confirmed occasion. There is confirmation that they are among the major uncertainties and dangers to the tourism sector (Gričar et al., 2022).

The Island Garden City of Samal (IGaCoS), contended to be the Philippines' largest resort city (ECCP, 2022), was not spared from the ill-effects of the pandemic. Data from the City Investment and Tourism Office revealed only 154,076 tourist arrivals in 2020, compared to 1,807,704 visits in 2019, a massive 91% decrease rate. All beach resort operations were crippled, receiving only a trickle of visitors who were mostly domestic. Fearing contamination, tourists primarily hinged their preferences upon safety (Botero et al., 2020; Wen et al., 2020).

To date, while there are plentiful studies that model tourist arrivals in many parts of the world, there is an utter scarcity— if not an absence— of research topics that delve into the subject matter in the Philippines, particularly in the Island Garden City of Samal (IGaCoS). Abing (2024) implied that the tourism industry is the main lifeblood of IGaCoS, the country's largest resort city (ECCP 2022). Accordingly, modeling tourist arrivals to have reliable predictions of tourists who will come to this serene, beach-fringed island at the heart of Davao Gulf is unquestionably necessary for a view of effective tourism planning and management— especially in the context of the post-pandemic recovery.

The purpose of this study is to model the tourist arrivals in the Island Garden City of Samal (IGaCos) from January 2017 to September 2023 by utilizing the ARIMA method in view of having a reliable prediction of the number of tourists who will visit this locality in the 4th quarter of 2023 to the 1st quarter of 2024.

Specifically, the study will attempt to answer the following objectives:

1) To determine the characteristics of the time series plot of tourist arrivals in IGaCoS from January 2017 to September 2023;
2) To ascertain whether the tourist arrivals in IGaCoS from January 2017 to September 2023 exhibit a stationary time series at level; and
3) To determine if there is a statistically appropriate forecasting model using the ARIMA approach, based on which it will be possible to reasonably forecast the number of tourists who will visit the Island Garden City of Samal from October 2023 to March 2024.

This study exclusively utilizes the ARIMA model of the Box-Jenkins methodology despite the availability of more advanced models like GARCH or hybrid approaches. While the latter may indeed capture short-term volatility and structural breaks better, the

ARIMA model remains sufficient for the objectives of this study. Its relative simplicity, ease of implementation, and focus on long-term trends and seasonal variations over short-term shocks make it suitable for tourism data, where such patterns are critical for business operations in the tourism-related industry. Furthermore, being a pure time series model, ARIMA does not make considerations for measuring the effect of external factors (or explanatory variables). Studies using secondary data are inherently limited by the readily available data. Hence, implications for policymakers may be limited, and as the research focuses on IGaCoS, the findings are unlikely to be generalizable, similar to other location-specific tourist arrival studies.

The significance of the study lies in its potential to enhance understanding and predict tourist arrivals in the Island Garden City of Samal, offering valuable insights for businesses in the tourism-related industry. By developing a sound model, this research enables businesses to have a roadmap to anticipate tourist demand fluctuations, optimize resource allocation, tailor marketing strategies, and improve overall operational efficiency. Consequently, businesses can better cater to tourists’ needs, enhance visitor experiences, and ultimately contribute to the sustainable growth and development of Samal Island’s tourism sector. Moreover, findings from this study may inform policy decision-makers in initiating investment strategies aimed at enhancing sustainable tourism development in the Island Garden City of Samal. Also, this may provide future researchers with a solid framework for analyzing tourism trends and methodologies for predictive analytics. It may offer a viable basis for comparative studies and the development of advanced forecasting models. Lastly, this study supports Sustainable Development Goal (SDG) No. 8 to promote inclusive and sustainable economic growth.

2. Literature Review

The tourism industry is indeed one of the largest and fastest-growing sectors of the global economy in the twenty-first century (Hossen et al., 2021; Zlatkou, 2021). For many countries, especially those that rely heavily on tourism, tourism is a major source of income that helps with overall economic development (Haryanto, 2020). In Spain, for instance, Rodrı´guez and Gallego (2020) noted that the growth of the tourist industry is a key factor in the creation of jobs and overall economic development. Moreover, it was pointed out by Kourentzes et al. (2021) that with global tourist arrivals increasing from 439 million in 1990 to 1.5 billion in 2019, the tourism industry has experienced consistent expansion over the past three decades.

In the Philippines, a beautiful tropical country where the tourism industry occupies an important role in the national economy (Andulana et al., 2021), there were only 1,323,956 international tourist arrivals in 2020 on account of the COVID-19 pandemic, a whopping 84% lower than 8,260,913 tourist visits in 2019 (Cordero, 2021). From PHP550.2 billion of international tourism receipts in 2019, it was projected to plummet down to PHP279.5 billion in 2020 (PricewaterhouseCoopers, 2020). Huynh et al. (2021) noted that these figures would represent a loss for the national tourism industry to around $US7 billion as the pandemic was persisting until the third quarter of 2020. To alleviate the situation, the PhP165 billion Bayanihan to Heal as One Act (R.A. No. 11469) was passed in August 2020, providing financial support to hit sectors badly (Yap, 2020).

Tourist arrivals have been the subject of various studies in several tourism-dependent countries. Anisa et al. (2021) commented that tourist arrivals remain to be the most acknowledged factor of tourism demand. Anent, precise calculation of the number of tourists who will visit a particular destination is an utter necessity for tourism planning (Li & Wu, 2019; Prastyadewi et al., 2023). Forecasting is, therefore, crucial for the tourism business, especially in nations where it is a major source of income (Rodrı´guez & Gallego, 2020). In view of this, proper tourist arrival modeling—and forecasting—directly support government and industry players in their decision-making, prevent waste and inefficiency of tourism capital, and lowers risk and uncertainty (Anisa et al., 2021). Decision-makers can improve the effectiveness of their strategic planning and lower the risk of poor decision-making by using reliable estimates of seasonal tourist flows (Diunugala & Mombeuil, 2020; Law et al., 2019; Polintan et al., 2023; Turtureanu et al., 2022). Since arrivals are a leading predictor of future demand, anticipating tourism flow in relation to arrivals is crucial for both tourism and the overall hospitality sector. Li and Wu (2019) were in the same vein, stressing that forecasting tourist visits is a crucial tool in tourism planning and policy-making, hence receiving particular interest from industry practitioners nowadays.

Yet, since uncertainty is inherent in predicting tourist demands, tourist arrivals easily succumb to the debilitating effect of unforeseen events like the COVID-19 health crisis (Turtureanu et al., 2022). In fact, 2020 was dubbed "the worst year on record" for travel due to a 74% decline in international visitor numbers worldwide. This resulted in a loss of US$1.3 trillion in receipts or 1 billion fewer visitors worldwide in 2020, which is an increase of more than 11 times the loss experienced during the global financial crisis of 2009 (Caynila et al., 2022). It was pointed out by Huynh et al. (2021) that, among businesses, tourism-related industry was the most susceptible to the pandemic. The tourism sector has suffered because of the travel restrictions put in place by all nations (Jaya & Sunengsih, 2022). So encompassing was its impact, which led Anu et al. (2022) to comment that due to COVID-19's restrictions on travel and tourism, practically every country and citizen in the world has had their lives altered. This dire situation leads some tourism scholars to view that research and discussions nowadays focus mainly on the COVID-19 pandemic- and tourist arrivals (Andulana et al., 2021). Accordingly, it is crucial that forecasting models for visitor arrivals are accurate (Diunugala & Mombeuil, 2020).

In forecasting demand in the tourism business, time series models are argued to be frequently used (Ghalehkhondabi et al., 2019). Time series models were generally utilized in modeling and forecasting tourist receipts (Abellana et al., 2021). Specifically, time series models use historical variations in variable(s) to forecast future values or occurrences. While the dependability of the estimated equation is typically based on out-of-sample prediction performance, time series models are not always based on economic theory, in contrast to structural models, which relate to the model at hand to forecast (Jackson & Tamuke, 2019). It has been cited that when there is a lot of data available for the variable we wish to forecast, such as tourist flows, time series models are typically employed (Diunugala & Mombeuil, 2020) since these frequently provide a more precise projection of tourist arrivals. In predicting tourist arrivals, time series models are known to generate more reliable and accurate forecasts (Jamal et al., 2019; Kaewmanee et al., 2021).

In this regard, it has been observed by some scholars that the ARIMA model is the most preferred statistical time series forecasting method which can provide reliable prediction (Bespalova, 2022; Makoni et al., 2023; Nyagadza & Chigora, 2022). Among the existing time series models, the ARIMA approach was argued to be widely used (Song et al., 2019; Zlatkou, 2021). ARIMA was one of the best time series models for forecasting tourist arrivals, which could even outperform econometric (causal) models (Bespalova, 2022). Numerous researchers have stressed the sheer dominance of the autoregressive integrated moving average (ARIMA) model and used it extensively to anticipate a range of variables, showcasing its capacity to predict outcomes reliably when all process conditions are met, especially when creating short-term forecasts (Bespalova, 2022; Makoni et al., 2023; Wu et al., 2021; Yang et al., 2023). For instance, Waluyo (2019) witnessed the primacy of ARIMA when forecasting tourist arrivals in Indonesia for a short-term period. Also, Ilmayasinta (2021) and Kiran & Reddy (2022) utilized –and noted— the good performance of the ARIMA model in predicting tourist arrivals for the next six months in Indonesia and India, respectively.

In the Philippines, Polintan et al. (2023) stressed that businesses and policymakers alike widely use ARIMA to forecast vital economic metrics, including tourist arrivals. All these studies attest to the high prominence of ARIMA in tourism data modeling and forecasting even in the presence of anomalies (Almeida et al., 2022) and, as a matter of fact, even in the context of the COVID-19 pandemic (Nagendrakumar, 2021; Velu et al., 2022). Meanwhile, approximately 75% of the 74 papers that Song et al. (2019) examined demonstrate that ARIMA models perform better than alternative methods when evaluating at least one destination and forecast horizon.

Nonetheless, there has been a consensus among the most notable scholars that no model can be considered as tailored fit for all occasions; no model has ever outperformed others in every situation (Abdou et al., 2021). In fact, after assiduously assessing around 211 published papers ranging from the year 1968 to 2018, Song et al. (2019) concluded that in terms of forecasting accuracy across all contexts and circumstances, no model can consistently outperform all others. That is why several scholars implied that a hybrid method for time series forecasting would be more advantageous. This idea was supported by Wu et al. (2021) and by Ghalehkhondabi (2019), stressing that hybrid methods are more effective in providing more accurate forecasts than their traditional counterparts. Nevertheless, Velu et al. (2022) pointed out that while the hybrid method would be better, some studies also maintain that traditional ones would do just fine. In other words, the hybrid model is not always a superior approach, though, in comparison to its basic time-series model projecting. Thus, this issue calls for a deeper inquiry into the subject of time series forecasting.

All these results support the conclusion made by Song et al. (2019), which stated that there is no perfect forecasting model that can be used in every situation. It can be claimed that the most accurate forecasting technique will ultimately depend on the circumstances (Bi et al., 2020); hence, the optimal model can be chosen based on the current situation and the data at hand (Eleni, 2020).

This study hinges on the Push-Pull theoretical framework proposed by Dann (1977). In tourist research, the sign-gestalt paradigm—also referred to as the "push-pull factor" theory—is the most widely accepted theory. As the driving force behind traveler behavior, motivation is a crucial topic of research (Sadhale & Sathe, 2020). The Push and Pull Factor Theory illuminates the intricate dynamics shaping tourist arrivals in destinations (Arowosafe et al., 2021; Guleria, 2019). The idea underlying the push and pull dimension is that individuals move because they are pulled in the direction of the desired attribute by outside influences and propelled in that direction by internal forces (Kyriakaki et al., 2020; Segal, 2019). On the one hand, the intangible or intrinsic wants of the individual traveler make up the majority of origin-related push factors that drive individuals to seek travel experiences (Michael et al., 2020). These consist of socioeconomic conditions, personal motivations, and cultural influences, among others. On the other hand, pull factors are those that arise because of a destination's perceived appeal by the visitor, encompassing the attractions and attributes of the destination itself— ranging from natural beauty and cultural heritage to infrastructure and events—entice tourists to visit specific locations (Arowosafe et al., 2021).

In the context of the COVID-19 pandemic, the Push and Pull Factor theory provides insights into the decline and abnormality of tourist arrivals. The Covid-19 pandemic has altered human routines and behavior (Mursalina et al., 2022). Meanwhile, Liu et al. (2021) observed that tourists typically alter their plans or even cut back on their travels during pandemics because of worries about unknown risks. Apparently, the pandemic triggered significant disruptions in both push and pull factors: push factors such as health concerns, travel restrictions, and economic uncertainty discouraged travel, while pull factors like closures of tourist attractions, hospitality shutdowns, and destination lockdowns made travel to tourist destinations unfeasible or undesirable. Gossling et al. (2021) iterated that these combined effects led to a dramatic decline in tourist arrivals globally, illustrating how external crises can disrupt the delicate balance between push and pull factors, resulting in abnormal fluctuations in tourist arrivals.

This study undertakes to determine the most appropriate ARIMA model, by which it would be possible to reliably predict future tourist arrivals in the Island Garden City of Samal (IGaCoS). The best ARIMA model will be determined through its forecasting accuracy. The number of tourist arrivals in the given time series will serve as the dependent variable in the fitted model (Bespalova, 2022; Jamal et al., 2019). Consequently, the result of this study would have relevant implications for business operations in the tourism-related industry in IGaCoS.

3. Material and Methods

3.1 Dataset

This research utilized quantitative secondary data (Mursalina et al., 2022; Velu et al., 2022). For studies using the Box and Jenkins procedure, a minimum of 50 observations are normally advised. This was to address seasonal changes and their impacts (Hassouna & Al-Sahili, 2020). Meanwhile, Gaetano (2022) viewed that 40-50 observations would be acceptable.

Table 1: Monthly Data of Tourist Arrivals in the Island Garden City of Samal from January 2017 to September 2023

	2017	2018	2019	2020	2021	2022	2023
January	113,136	104,567	167,229	58,971	355	79,540	56,456
February	67,022	84,057	129,790	36,759	1,143	66,872	55,431
March	91,281	138,977	152,663	1,940	60,323	63,772	60,921
April	178,454	184,272	231,906	0	94,261	94,460	101,085
May	170,518	188,014	243,307	0	88,404	71,160	96,977
June	124,005	124,106	139,766	0	5,193	63,584	83,728
July	78,047	111,223	117,487	0	21,970	69,344	96,335
August	77,371	119,496	124,002	7,700	64,262	67,230	95,053
September	72,400	98,302	98,517	13,525	37,471	48,888	56,220
October	84,014	109,422	107,378	12,282	59,425	42,107	
November	97,023	140,219	121,892	11,991	100,860	38,956	
December	160,722	180,286	173,767	10,908	133,365	73,837	
Total	**1,313,993**	**1,582,941**	**1,807,704**	**154,076**	**667,032**	**779,750**	**702,206**

Source: City Investment and Tourism Office (LGU- IGaCoS).

To meet said qualification, 81 monthly data of international and domestic tourist arrivals in the Island Garden City of Samal (IGaCoS) from January 2017 to September 2023 were obtained from the City Investment and Tourism Office of LGU- IGaCoS. In this study, the monthly tourist arrival figures from January 2017 to June 2020 were used as the model estimation sample, while data from July 2020 to September 2023 were reserved for validation and performance evaluation of the forecasting model. Meanwhile, the GNU Regression, Econometrics, and Time-series Library (Gretl), a well-recognized and dependable statistical program, was employed for data analysis to accomplish the objectives stated in this paper.

3.2 Design and Procedure

This study utilized a quantitative method of tourism forecasting (Turtureanu et al., 2022). To achieve the goals of this study, the researcher employed the Box-Jenkins ARIMA model, a predictive research methodology (Polintan et al., 2023), as it is a widely utilized modeling technique that uses past data to forecast visitor arrivals in the future for any time series variable (Nagendrakumar, 2021; Song et al., 2019; Zlatkou, 2021). This methodology was appropriate for the research since it used a methodical approach to analyze and forecast time series data.

3.2.1 Box-Jenkins Procedure

The Box-Jenkins procedure was employed to select the best ARIMA model for the purpose of this research (Msofe & Mbago, 2019; Polintan et al., 2023). Commonly known as Box-Jenkins methodology after George E. P. Box and Gwilym M. Jenkins (Chipumuro & Chikobvu, 2022; Lip & Anuar, 2020), the univariate ARIMA (*p, d, q*) model is of the equation (Velu et al., 2022):

$$y_t = \vartheta_0 + \varphi_1 y_{t-1} + \cdots + \varphi_p y_{t-p} + \varepsilon_y - \vartheta_1 \varepsilon_{t-1} - \cdots - \vartheta_q \varepsilon_{t-q}$$

where,
p is the order of the non-seasonal autoregressive component,
d is the order of process integration,
q is the order of the non-seasonal moving average component.

Ete et al. (2020) identified four steps of the Box-Jenkins methodology as follows:

1) **Model Identification.** ARIMA models are delineated for stationarity. Hence, it is necessary to determine whether the observed time series is stationary or not (Fatima et al., 2022). To proceed to model building, it is important to first ascertain the stationarity since misidentification of data transformation can subsequently lead to erroneous results and interpretations (Zhang et al., 2022). The stationarity of the time series was measured using a time plot and an augmented Dickey-Fuller (ADF) unit root test (Msofe & Mbago, 2019). Data are said to be stationary if they have a small p-value, usually <0.05 (Tan et al., 2022). If the time series is non-stationary, it will be transformed to stationary using the differencing technique (Chipumuro & Chikobvu, 2022).
2) **Parameter Estimation.** In this step, the ARIMA (*p,d,q*) model order was tentatively identified by determining the values of *p, d,* and *q*. Msofe and Mbago (2019) hinted that model identification in time series is particularly challenging, and trial and error is typically employed. The values chosen for *p, d, q* should typically be less than or equal to two. For this purpose, an examination of the significant lags in the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) diagram will be undertaken (Agada et al., 2021; Imam, 2020; Priyadarshini et al., 2022).
3) **Diagnostic Checking.** This phase consisted of checking whether the information in the time series data has been properly represented by the fitted model. In other words, this was to establish the adequacy of the selected model. Pertinent statistical tests will be utilized in this regard (Thushara et al., 2019). By way of comparison, the model with the lowest Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values is the best-fit model (Subramaniam & Muthukumar, 2020). Meanwhile, Chipumuro and Chikobvu (2022) conjectured

that the ARIMA model's forecasting accuracy is measured through its Mean Absolute Percentage Error (MAPE). If the fitted model is deemed inadequate, the researcher must repeat the same process from step 1 until the diagnostic test is finally passed.

4) **Forecasting.** This step was the ultimate intent of the modelling process after ascertaining the selected model has met both the parameter significance test and model conformity test. This would accordingly facilitate the achievement of the objectives of this research.

3.3 Ethical Considerations

In the conduct of research, ethical considerations were paramount. This study made it certain to abide by the ethical guidelines set by the University of Mindanao Ethics Review Committee (UMERC), as evidenced by UMERC Protocol No. 2023-410.

4. Results and Discussion

4.1 Time Series Plot of Tourist Arrivals in IGaCoS

Figure 1 presented a thorough visual representation of the monthly arrivals of visitors throughout time in the Island Garden City of Samal for the period of January 2017 to September 2023. The figure displayed the actual visitor arrivals on the vertical axis (y-axis), and the horizontal axis (x-axis) showed the sequential timeline during the course of 81 months of observation. The time series revealed a steady, gradual increase up until 2020. This was evidenced by 1,313,993 arrivals in 2017, 1,582,941 in 2018, and 1,807,704 in 2019. Next, a sharp decline was observed midway through 2020. Notably, the COVID-19 pandemic's noticeable effects were quite apparent, and there was a sharp drop in tourist numbers starting in March 2020. In fact, zero arrivals were recorded from April 2020 to July 2020. In total, there were only 154,076 tourist arrivals in 2020, a whopping 92% lower than 1,807,704 tourist visits in 2019. A gradual increase was noted once more, starting in 2021, with some fluctuations. There were 667,032 and 779,750 arrivals recorded for 2021 and 2022, respectively. The latter constitutes around an encouraging 400% increase rate.

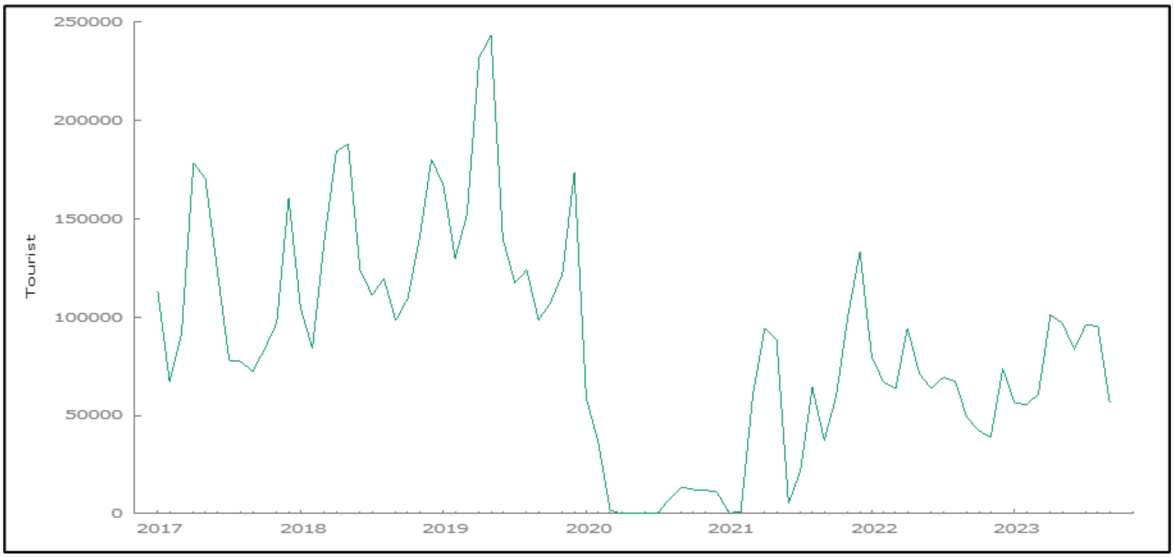

Figure 1: Status of Tourist Arrivals in Island Garden City of Samal from January 2017 to September 2023

Additionally, patterns showed up within the overall trajectory. These patterns were most prominently characterized by an apparent increasing trend combined with intermittent sinusoidal oscillations, which are suggestive of seasonal changes within the time series plot of tourist arrivals. It is crucial to emphasize that the existence of such pronounced trends and periodic fluctuations may indicate non-stationarity in the data, hence requiring suitable statistical methods for both analysis and modeling. Two characteristics were displayed in the time series. There was an initial increase in tourist arrivals followed by a sharp decrease in the number of tourists starting in March 2020, indicating the impact of the COVID-19 epidemic. Then, there was another gradual increase in arrivals starting in 2021, indicating post-pandemic recovery.

The Island Garden City of Samal has been known for being a tourist haven in the South, thanks to its natural beauty and attractions (Atasoy et al., 2022). This explains the increasing trend of tourist arrivals from 2017 to 2019. Unfortunately, this auspicious increasing trend was not sustained as IGaCoS, a tranquil, beach-fringed island, succumbed to the ill effects of the pandemic. All tourist resort operations were crippled, receiving only a trickle of visitors who were mostly domestic in 2020. Fearing contamination, tourists primarily hinged their preferences upon safety, suggested Botero et al. (2020) and Wen et al. (2020). The degree of this reduction underscores the striking impact of the pandemic on the tourism sector in IGaCoS.

This extraordinary decline reflects the severe travel restrictions (as per Executive Order Nos. 206 & 207 series of 2020) put in place by the local government of IGaCoS in the wake of the epidemic, which resulted in a startling halt to tourist activity for a continuous period of four months. This finding finds connection with the empirical evidence of several studies (Bakar & Rosbi, 2020; Esquivas et al., 2021; Huynh et al., 2021; Jaya & Sunengsih, 2022; Lin, 2023; Sigala, 2020; Turtureanu et al., 2022).

Moreover, most of the tourist resorts in IGaCoS belong to the small and medium enterprises category. It has been observed that the larger impact of the pandemic falls on smaller businesses (Bartik et al., 2020; Hu et al., 2021; International Trade Center, 2020; Sonobe et al., 2021). In Vietnam, Nguyen (2020) noted that, unlike big tourism enterprises, which are arguably more resilient to crisis, small businesses are more susceptible to shutdown or bankruptcy. Similarly, in Poland, Wieprow and Gawlik (2021) noted that although the COVID-19 pandemic impacts all levels of tourism enterprises, the medium- and small-sized companies are at a more severe disadvantage. In Mauritius, Jaffur et al. (2022) observed the same matter.

With almost all tourism activities halted the City Government of the Island Garden City of Samal found itself in deep waters, trying to figure out how to revive its tourism industry amidst the COVID-19 pandemic. Nevertheless, the situation is not without remedy. Amid darkness, there is always a glimmer of hope. Highly dependent on tourism-related income, the local government deemed it necessary to reopen tourism in this locality amidst the pandemic, albeit on restricted measures. That is why at the very first hint by the Regional Inter-Agency Task Force for Emerging Infectious Diseases (IATF-EID) allowing the resumption of limited tourism activities on the Island, City Mayor Al David T. Uy signed Executive Order No. 277, permitting accredited establishments and resorts to resume their operations, subject to minimum health and safety standards.

This action by the local chief executive can be traced to the existing literature. Zielinski and Botero (2020) indicated that many governments decided to reopen tourist resorts as soon as the number of illness cases dropped because of the economic significance of tourism for many areas. Huynh et al. (2021) explained that all government instrumentalities should be more assiduous in prioritizing tourism policies, which could alleviate and strengthen the speedy recovery of all tourism-related businesses, which, in effect, could help establish resiliency. Anent, in 2021 and in 2022, a significant rebound in tourist arrivals can be observed, which is highly indicative of a possible post-pandemic recovery. This reflected what Tourism Economics stressed: while international travel may still take two to three years to recover, domestic travel may rebound in 2021 (OECD, 2020).

4.2 Stationarity Test of the Time Series at Level

Table 2 conveyed the statistical results from the stationarity test, specifically the Augmented Dickey-Fuller Unit Root Test, conducted on tourist arrivals data in the Island Garden City of Samal from January 2017 to September 2023. In a time series analysis, stationarity is a crucial prerequisite for forecasting accuracy.

In the testing, three situations were taken into account: one with a constant, one with a constant and trend, and one with a constant, linear, and quadratic trend. The test was administered at level, following one and two rounds of differencing in each scenario. The asymptotic p-value and τ (tau) statistic serve as representations of the stationarity test results.

Firstly, with a constant, the series is not not-level stationary, indicated by a p-value of 0.4165 (greater than 0.05) and τ-value of -1.7291. After one differencing, the series becomes stationary with a p-value of 0.01228 (less than 0.05) and τ-value of -3.36409. Further differencing confirms stationarity, with a τ-value continuing to decrease and a p-value less than 0.001. Next, with a constant and trend, non-stationarity at the level is indicated by a p-value of 0.4978 and a τ-value of -2.1844. After one differencing, the series remains non-stationary with a τ-value of -3.31264 and a p-value of 0.06413 (still over 0.05). Stationarity is achieved after two rounds of differencing, as shown by a p-value dropping to less than 0.001. Thirdly, with a constant, linear and quadratic trend, the series is non-stationary at the level and after one differencing, as p-values are greater than 0.05.

Table 2: Stationarity Test of Tourist Arrivals in Island Garden City of Samal from January 2017 to September 2023

Stationarity Tests	At level		Differenced once		Differenced twice	
	τ	Asymptotic p-value	τ	Asymptotic p-value	τ	Asymptotic p-value
With constant	-1.7291	0.4165	-3.36409	0.01228*	-8.62021	<0.001
With constant and trend	-2.1844	0.4978	-3.31264	0.06413	-8.54624	<0.001
With constant, linear and quadratic trend	-2.4680	0.5868	-3.39936	0.1405	-8.4796	<0.001

For an ARIMA modelling to work, the input time series must either be stationary or undergo differencing to become stationary (Hussain, 2021; Zhang et al., 2022). It is a necessary requisite because accurate forecasting depends on stationarity, which underscores that the data's mean and variance remain constant throughout time (Centeno & Marquez, 2020; Ryan et al., 2023). The time series is said to be stationary if the p-value is minimal, usually ≤ 0.05 (Tan et al., 2022). In the testing, based on Table 2, three situations were considered: one with a constant, one with a constant and trend, and one with a constant, linear, and quadratic trend. With a p-value of 0.4165, 0.4978 and 0.5868 for each of the three cases, respectively, initial statistical tests do reveal that the original data is not level-stationary but can be made stationary through differencing. In this study, the time series became stationary only after being differenced twice, confirmed by a p-value less than 0.001.

This finding is in consonance with the studies of Upadhayaya (2021) and Msofe & Mbago (2019). More importantly, this result provides an answer to the second objective of this study. At the level, the time series of tourist arrivals in IGaCoS from January 2017 to September 2023 does not exhibit stationarity.

4.3 Model Parameters Estimation and Diagnostic Checking

The autocorrelation and partial autocorrelation functions of the time-series data were statistically presented in Table 3. These results contributed to our understanding of the interaction between observations at different delays and helped identify the right parameters for the ARIMA model.

After achieving stationarity, the next step was to identify the most appropriate autoregressive integrated moving average model ARIMA (*p*,*d*,*q*) model. To find out the appropriate values of AR (q) and MA (p) parameters, examining both the PACF and ACF values was undertaken respectively (Fatima et al., 2022; Kiran & Reddy, 2022; Velos et al., 2020). It was postulated by Nagendrakumar (2021) that PACF is the source of the AR component, whereas ACF is of the MA component.

Based on the correlogram result in Table 3, it is notable that both ACF and PACF have very significant values in the first lag, which eventually dies down and cuts off, suggesting AR(p) = 1 and MA(q) = 1. This evidence was signified by (Nwokike et al., 2020). Furthermore, since the time series underwent two rounds of differencing, this indicated d = 2. Thus, the resulting model ARIMA (1, 2, 1), was identical to the one utilized by Zlatkou (2021) in forecasting tourist arrivals in Greece.

Table 3: Correlogram Results of the Time-series Data

Lag	ACF	PACF
1	0.7929 ***	0.7929 ***
2	0.5745 ***	-0.1460
3	0.5152 ***	0.2997 ***
4	0.5291 ***	0.1243
5	0.4645 ***	-0.1036
6	0.4145 ***	0.1544
7	0.4408 ***	0.1314
8	0.3873 ***	-0.2298 **
9	0.2310 **	-0.1605
10	0.1457	0.0555
11	0.1957 *	0.0915
12	0.2083 *	-0.0658
13	0.0809	0.2108 *
14	-0.0540	-0.1507
15	-0.0687	0.0757
16	-0.0262	0.1708

The statistical findings for an ARIMA model fitted to the selected period in the time-series data are displayed in Table 4. Phi's coefficient (-0.298894) and low p-value (0.0145) showed a significant negative effect from past values. Theta's coefficient (-1.00000) and very low p-value (<0.0001) indicated a significant impact from past errors. The standard errors for Phi (0.122313) and Theta (0.195730) suggested accurate estimates, unlike the constant's high standard error (4616.57). The model's R-square (0.077666) and adjusted R-squared (0.060896) indicated it explained about 7.77% of the variability. The log-likelihood (-731.6305) and moderate information criteria values suggested a reasonable model fit. The AR root (-3.3457) showed a seasonal pattern every 2 periods, while the MA root (1.0000) showed no additional seasonal pattern. The value of AIC (1471.261) and BIC (1479.433), being the lowest among the optimal orders, signified that the chosen model is the best-fit model to do the forecasting.

There are notable correlations between the moving average (MA) parameter (Theta) and the autoregressive (AR) parameter (Phi) with prior observations. Theta's (-1.00000) negative coefficient denotes a negative relationship with previous errors or residuals, whereas Phi's (-0.298894) negative coefficient reveals a negative linkage with prior values. With their relatively small standard error values of 0.122313 and 0.195730, the model's autoregressive and moving average components can be considered as essential for comprehending the behavior of the dependent variable. This signifies that there is confidence in the values of these coefficients and that the estimates are fairly correct. Also, both AR and MA parameters have p-values lower than 0.05, at 0.0145 and <0.0001, respectively. Theta and Phi's low p-values indicates statistical significance, that is, their coefficients have a substantial impact on the model, implying that errors and observations from the past have a substantial influence on the dependent variable's current value. In this regard, it is advantageous to leverage the significant AR and MA parameters in lieu of forecasting robustness and capability of the model. This result finds trace in the study of Yollanda and Devianto (2020).

Table 4: Diagnostic Check Results

	Coefficient	**Std. Error**	**z**	**p-value**	
(Constant)	3871.96	4616.57	0.8387	0.4016	
Phi (Φ)	−0.298894	0.122313	−2.444	0.0145	**
Theta (Θ)	−1.00000	0.195730	−5.109	<0.0001	***

Mean dependent var	−5795.474	S.D. dependent var	133035.6
Mean of innovations	−13794.16	S.D. of innovations	71454.12
R-squared	0.077666	Adjusted R-squared	0.060896
Log-likelihood	−731.6305	AIC	1471.261
BIC	1479.433	Hannan-Quinn	1474.437
MAE	31377.02	MSE	1728251043
MAPE	35.89%	RMSE	41572.24

		Real	**Imaginary**	**Modulus**	**Frequency**
AR (seasonal)					
	Root 1	-3.3457	0.0000	3.3457	0.5000
MA (seasonal)					
	Root 1	1.0000	0.0000	1.0000	0.0000

Another thing to consider on assessing the statistical significance of the coefficients of the AR and MA parameters is by examining their corresponding z-values. The z-values aid in determining the coefficients' statistical significance. If the absolute value of the z-value is greater than 1.96, a coefficient is deemed statistically significant at the 5% level. As highlighted in Table 4, Phi and Theta have negative z-values of -2.444 and -5.109, respectively. These values have considerable deviations from zero. At the standard significance level of 5%, AR and MA parameters appear to be statistically significant, with absolute z-values considerably higher than 1.96. Priyadarshini et al. (2022) hypothesized that parameters of AR and MA, which significantly differ from zero, are indicative of a good model fit. Meanwhile, Zhang (2022) pointed out that when the z-value is high, it means that there is little variation between the real and fitted values, making the prediction more accurate.

Moreover, examining the roots of AR and MA components can aid in providing insights into the patterns captured by the model, which is vital for appropriate data modeling. Bhowmik (2020) and Jackson & Tamuke (2019) viewed that an ARIMA forecasting model is stable, covariance stationary and invertible if the AR and MA inverted root values are less than one, lying within unit root polynomial or unit circle. In this case, the absolute value of the inverted root of the autoregressive parameter (AR) is 0.2988 (reciprocal of the original root -3.3457). Apparently, this value, being less than one, lies within the unit circle, implying covariance stationary. This is the same with the moving average (MA), though whose real root is one but whose imaginary root lies within the unit circle. In this case, the MA can be considered invertible if no additional roots were provided. Additionally, the invertibility of MA component depends on whether its lag coefficients lie outside the unit circle in the complex plane. For a MA (1) model, there is only one lag coefficient. Since the lag coefficient in this case is 1, its absolute value is 1. While being on the unit circle is a borderline case, it is generally considered that the MA component is invertible. This is because there is no guarantee that the series can be perfectly expressed as a function of past errors without any future dependence. These results are coherent with the studies of Nagendrakumar (2021) and Polintan et al. (2023) who conjectured that ARIMA models which are covariance stationary and invertible are fit for forecasting purposes.

As to the accuracy of the forecasted results, Chipumuro and Chikobvu (2022), as well as Angelaccio (2019), based their measurement on the value of the Mean Absolute Percentage Error (MAPE). Meanwhile, Diunugala and Mombeuil (2020) asserted that MAPE between 20-50 % signifies reasonable forecasting. In this particular study, the value of MAPE is 35.89%.

Since the diagnostic tests reveal that the parameter components are significant, and the model is both covariance stationary and invertible, and given that it has the lowest AIC, BIC and MAPE values, it can be concluded that the ARIMA (1,2,1) model is suitable and adequate for the time series. Therefore, ARIMA (1,2,1) is utilized to obtain a reasonable forecast of tourist arrivals in the Island Garden City of Samal for the period of October 2023 to March 2024. With this result, the third objective of this study is attained.

4.4 Model Fitting and Forecasting

The fitted ARIMA model was shown in Figure 2. It was trained using data from January 2017 to June 2020 and assessed using different data from July 2020 to September 2023. The model initially showed some deviations from the original data. At first, the trained ARIMA model tended to anticipate tourism demand just above real values and subsequently forecasts arrivals below actual values. But with time, it converged closely to the actual values, proving that it is a reliable way to represent underlying patterns.

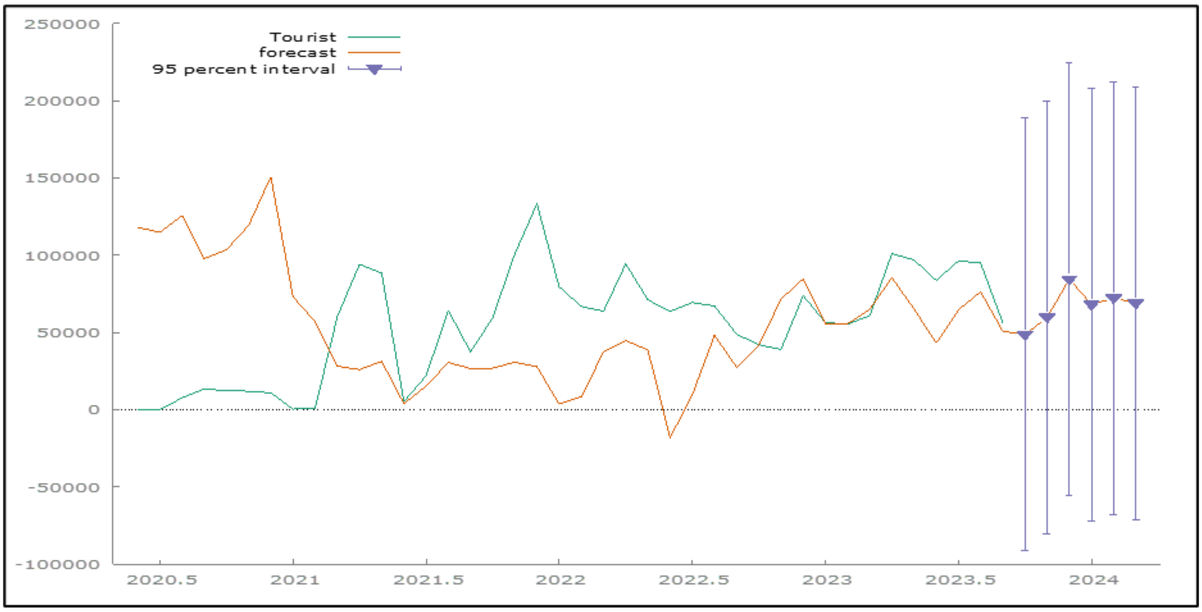

Figure 2: Model Fitting and Forecasting Applying ARIMA(1,2,1)

While several scholars are unanimous as to the sheer superiority of the ARIMA model especially when generating short-term forecasts (Bespalova, 2022; Makoni et al., 2023; Wu et al., 2021; Yang et al., 2023), even in the presence of anomalies (Almeida et al., 2022) and, as a matter of fact, even in the context of the COVID-19 pandemic (Nagendrakumar, 2021; Velu et al., 2022), the fitted model in this study has arguably encountered some difficulties in generating predictions with minimal errors, possibly because of a structural break in the time series.

The notable initial difference between the projected and actual number of visitors suggests that the COVID-19 pandemic, which resulted in several lockdown measures, had a negative impact on the Island Garden City of Samal's tourism sector. Similarly, this finding can be observed in the study of Chipumuro and Chikobvu (2022), who underscored that the initial disparity between the predicted and actual figures can be attributed to the uncertainties wrought by the COVID-19 pandemic, which had severely impacted the entire tourism industry. In this regard, Velu et al. (2022) strongly commented that even though it performed more accurately when assuming there was no COVID-19 pandemic from the start, the ARIMA model's implementation has not done well in forecasting the number of tourist arrivals in selected ASEAN countries. Some predictions even have negative values—an observation replicated in this study. Although it may be ruled out by removing these variables, it might indicate that further modifications are needed to make the prediction model better.

This now highlights the essence of taking into serious consideration the emergence of hybrid forecasting models, including artificial intelligence as emphasized by Höpken et al. (2021), to address inherent limitations of individual methods by incorporating structural changes and other exogenous factors for better predicting accuracy (Jackson & Tamuke, 2019; Wu et al., 2021). All these results support the conclusion made by Song et al. (2019), which stated that there is no perfect forecasting model that can be used in every situation. It can be claimed that the most accurate forecasting technique will ultimately depend on the circumstances (Bi et al., 2020); hence, the optimal model can be chosen based on the current situation and the data at hand (Eleni, 2020).

However, as time progresses, a notable trend emerges: the fitted ARIMA (1,2,1) model gradually aligns more closely with the actual values, capturing the behavior of the time series. This convergence pattern underscores the model's capacity to effectively capture and represent the underlying patterns inherent in the data. Thus, despite the initial disparities, the ARIMA (1,2,1) ultimately proves its reliability as a robust tool for predicting tourist arrivals in the Island Garden City of Samal.

Finally, the dashed lines in the graph's rightmost section showed the estimated visitor arrivals figures for the next six months and a 95% confidence range. Notably, there was a noticeable upward trajectory at the beginning, followed by a slight decline at the end that remained stable.

4.5 Forecasted Values of Tourist Arrivals in IGaCoS

The forecasted values were presented in Table 5, along with a 95% confidence interval for each month from the last quarter of 2023 to the first quarter of 2024. In October 2023, the forecasted value was 48,639. Around 22.94% increase is expected in November 2023, with 59,831 arrivals. In December 2023, the forecasted value jumped significantly to 84,604, a whopping 41.40% growth from the previous month. However, in January 2024, the forecasted value decreased slightly to 68,141, albeit remains relatively high. This comprises around a 19.44% reduction compared to the peak season in December. Then, in February 2024, the forecasted values surged again to 72,296, a significant recovery from the decrease observed in January. Finally, in March 2024, the forecasted value falls slightly to 69,067, although remaining stable.

Table 5: Forecast Values for the Next Six Months Applying ARIMA(1,2,1)

Month	**Forecast (95% C.I.)**
October 2023	48,639
November 2023	59,831
December 2023	84,604
January 2024	68,141
February 2024	72,296
March 2024	69,067

The ARIMA (1,2,1) model is used to forecast tourist arrivals in the Island Garden City of Samal from October 2023 to March 2024, a six-month timeframe. Cuhadar (2020), Jackson & Tamuke (2019), and Šenková et al. (2021) observed the versatility and accuracy of ARIMA model when utilized for short-term forecasting. This underscores, though, that risks are identified to handle ambiguity surrounding short-term timeframes. For instance, Ilmayasinta (2021) and Kiran & Reddy (2022) employed a six-month timeline when forecasting tourist arrivals in Indonesia and India, respectively.

As presented in Table 5, ARIMA (1,2,1) offers informative projections for the number of tourists expected to visit Samal Island Garden City for the next six months. In general, it signifies a curious mix of fluctuations and stability. There is a remarkable increasing trend, yet a slight fluctuation can be observed in the months of January 2024 and March 2024. With an anticipated value of 48,639 in October 2023, a minor increase is anticipated, suggesting a possible rebound from shocks like the COVID-19 pandemic. November 2023 witnesses a significant increase to 59,831, maybe due to favorable travel circumstances or seasonal factors that encourage more tourists. Then, there is a significant uptick at 41.4% in December 2023, with a peak of 84,604, which corresponds with normal holiday travel patterns, particularly the Christmas season, and strengthens the city's appeal as a leisure destination.

The predicted figure slightly drops to 68,141 in January 2024, maybe indicating post-holiday slowdowns, but then rises to 72,296 in February 2024, indicating a post-holiday upsurge in tourist activity. The tourism industry in Samal Island Garden City is resilient and consistently engages visitors, as evidenced by the anticipated value of 69,067 for March 2024, which indicates stability. In this regard, local government should be assiduous in taking appropriate measures towards sustainable tourism development (Malangalila & Mhache, 2023).

4.6 Implications to Business Operations of Tourism-Related Industry

The forecasted results from the ARIMA (1,2,1) model offer valuable insights for businesses belonging to the tourism industry in Samal Island. These perceptions hold significant theoretical and practical implications— in fact, a roadmap— for comprehensive planning and operations. The apparent fluctuation of tourist arrivals has a great significance in both operational and strategic planning of tourism-related businesses (Anisa et al., 2021; Diunugala & Mombeuil, 2020; Law et al., 2019).

To effectively manage the inherent fluctuations in tourist arrivals, tourism-related businesses must adopt flexible operational strategies that significantly enhance their adaptability and resilience. This includes implementing dynamic staffing arrangements that adjust workforce levels in response to tourist demand, thereby optimizing labor costs and service delivery. Leveraging dynamic pricing strategies can attract visitors during off-peak seasons, maximizing revenue opportunities (Murodova, 2024). Additionally, optimizing inventory management minimizes waste and ensures that both perishable and non-perishable goods align with real-time demand. Strategic resource allocation, informed by real-time data, ensures that transportation, accommodation, and recreational services are scaled appropriately. Also, collaborating with local businesses to maintain a responsive supply chain further enhances operational efficiency (Lakshmi et al., 2024). Utilizing advanced technology and data analytics to monitor and predict tourist trends is crucial as well for timely adjustments, while maintaining consistent customer experience management ensures high service quality regardless of tourist volumes.

Moreover, tourism businesses should engage in comprehensive market research and trend analysis to forecast long-term fluctuations and prepare accordingly, iterated (Ke, 2024). Another important thing Mammen et al. (2019) underscored is that diversifying product and service offerings to appeal to various market segments reduces dependency on a single demographic, thereby spreading the risk. Developing robust risk management and contingency plans can mitigate the impacts of potential downturns, including establishing financial reserves and alternative revenue streams. Marketing efforts through leveraging social media and digital technology should focus on generating demand during off-peak periods while forming strategic partnerships with travel agencies, airlines, and other stakeholders can help ensure a steady flow of tourists. Tourism businesses may positively capitalize on downtimes to renovate facilities and improve services, as observed by Dalagan and Sy (2023) among beach resorts in IGaCoS— a true emblem of resilience and adaptability in the post-pandemic recovery. Rosli and Jamil (2020) pointed out that each business should take proactive steps to start their self-adjustment plan so they can weather any crisis. This reaffirmed the important role that tourism businesses play in reviving their capacity for economic growth rather than pure reliance on government assistance.

5. Recommendations

Based on the results of this study, tourism-related businesses in the Island Garden City of Samal can take actionable steps to optimize operation, capitalize on growth opportunities and ultimately maximize customer satisfaction. This indicates developing a comprehensive business plan, considering both peak and off-season periods. This plan should address staffing concerns, inventory management, facilities/equipment maintenance, marketing strategies and resource allocation, among others, throughout the year. On the one hand, during peak months like November and December, businesses can prepare for the higher influx of tourists by increasing resources. They should prepare for this by staffing up, managing inventory effectively and offering targeted promotions via digital technology to maximize tourist receipts. On the other hand, during slower months like January, focusing on promotional resources and exploring niche markets or developing tourist-drawing attractions would be very advantageous. Also, businesses may create special offers for these months, develop tourist-drawing attractions and implement loyalty programs.

Local government policymakers, to better support the tourism industry amidst tourist arrival fluctuations and business uncertainty, should initiate an appropriate fiscal policy response and financing scheme. More importantly, to sustain the development of tourism-related industry in Samal Island, policymakers should focus on advancing sustainable tourism, with a special focus on overcoming obstacles during the post-pandemic recovery. This signifies a holistic approach that balances economic growth with environmental and social sustainability. Promoting responsible tourism practices through intensive education and awareness campaigns can help tourists understand the importance of valuing local customs, wildlife and ecosystems—safeguarding destinations for future generations. Also, it would be very advantageous to determine the carrying capacity of Samal Island and develop strategies for sustainable tourism growth. Investment in tourism infrastructure, particularly road networks— including even the materialization of the connector bridge with mainland Davao— is vital to resuscitate the tourism industry spoiled by the ill-effects of the pandemic.

Future researchers may explore alternative forecasting models that integrate significant exogenous factors (or explanatory variables) that affect the behavior of a particular time series. Even though the predicted values are categorized as reasonable forecasts, and the proposed ARIMA model's accuracy can be considered good, the model is still not very accurate, most likely because there was a significant structural break during the sample period. Although ARIMA models have been effective in modeling tourism data, it is important to explore other models, such as ARCH and GARCH, which account for non-constant variance (or volatility) in time series data. Also, exploring ARIMAX would be advantageous because it can include exogenous variables. Additionally, hybrid models should be considered when analyzing tourism datasets. Models that incorporate elements related to risk and uncertainty are essential, as they can help develop more resilient models capable of handling potential shocks or disruptions, such as future pandemics, as seen with COVID-19. Lastly, by employing multivariate or hybrid models, and even Artificial Intelligence (AI) such as machine learning models or deep learning models, future studies may better capture complex patterns in the time series and obtain more accurate predictions of tourist arrivals in the Island Garden City of Samal.

6. Conclusion

The analysis of the time series produced several key findings. Firstly, the analysis revealed an initial increasing trend and fluctuation, particularly a sharp decline starting in March 2020 attributable to the COVID-19 pandemic, followed by a gradual recovery. This decline was a result of stringent travel restrictions and had a significant impact on the tourism industry.

Also, the investigation identified seasonal variations in the data, indicating the presence of both trend and seasonality. The ADF test confirmed that this level's time series is not stationary. The study highlighted the importance of addressing non-stationarity in the time series data before proceeding with modelling. The non-stationarity of the original time series data was addressed through differencing. The time series became stationary after being differenced twice.

Parameters of the ARIMA model were estimated by examining the correlogram result, leading to the identification of ARIMA(1,2,1) model. After diagnostic checking, the model was found to be suitable for forecasting tourist arrivals in the Island Garden City of Samal from 2023 (4^{th} quarter) to 2024 (1^{st} quarter). With a MAPE of 35.89%, the model was assessed to have a reasonable forecasting accuracy. It was highlighted that structural changes, like the occurrence of a pandemic, may account for the initial disparities between forecasted values and actual figures. This implies that the proposed model, univariate ARIMA (1,2,1), has encountered some difficulties in generating predictions with minimal errors, possibly because of several structural breaks in the time series. Future directions of this research may, therefore explore other forecasting models which have greater forecasting capacity in terms of accuracy by incorporating volatility and other incorporating external factors (or explanatory variables), such as multivariate or hybrid models.

Nonetheless, the ARIMA(1,2,1) model gradually exhibited a convergence with the actual values (except some extreme ones) over time, indicating its capacity to capture the underlying patterns in the data. The forecasted results suggest a mix of fluctuations and stability, aiding tourism-related business operators in planning strategically and optimizing their operations. It is indicated that an increasing trend would occur starting in October 2023 and peaking in December 2023, with visitors expected to be around 84,604, a whopping 41.4% increase from the previous month. Nevertheless, apparent fluctuations would be expected in the first quarter of 2024. Businesses can leverage this to adjust staffing, inventory, supply chain, marketing efforts, and resource allocation while exploring innovation, collaboration, and diversification opportunities.

Notwithstanding the relative robustness of the ARIMA model, it is essential to use the forecast only as the baseline in consideration of other factors for informed decision-making. While these findings and insights may provide a roadmap for tourism-related businesses to optimize operations and capitalize on growth opportunities, it is always advantageous to approach forecasted data with caution and common sense, considering other exogenous factors and the overall business volatility. Therefore, continual flexibility and adaptation are essential for tourism stakeholders to respond effectively to evolving- and uncertain- circumstances.

Accordingly, the results of this study confirm the theory on which this research is anchored. The constant fluctuation of tourist arrivals in the time series can be understood within the realm of the Push-Pull theoretical framework introduced by Dann in 1977, wherein a tourist’s decision to visit a particular destination is primarily determined by motivations (push factors) and perceptions (pull factors). Fluctuations occur as tourists’ preferences, perceptions, and external circumstances change over time, influencing their decisions to visit or avoid specific destinations. This dynamic interaction creates long-term trends and short-term fluctuations in tourist destination visitation. In effect, even if a perfect forecasting model is found, it can only approximate complex tourist behaviors since decisions made by visitors may reflect shifting preferences, motivations or even economic shocks.

Acknowledgements
The researchers would like to thank Dr. Rosalia T. Gabronino, Dr. Vicente Salvador E. Montaño, Dr. Reynaldo C. Castro and Dr. Joel B. Tan for their constructive feedback and critical suggestions, which greatly enhanced the quality of this work. Lastly, the

researchers profoundly acknowledge the divine wisdom and guidance that the Omnipotent God has bestowed on His mere creatures, bringing this research undertaking to completion.

Conflict of Interest Statement

The authors declare no conflicts of interest.

About the Author(s)

Lemuel B. Asdang serves as an internal auditor for the local government of the Island Garden City of Samal, Philippines. He is currently pursuing an MBA at the University of Mindanao in Davao City, Philippines.

Stilo Floyd F. Schneider, PhD, DBA, is a faculty member at the University of Mindanao with notable expertise in business administration studies, where he currently serves as the Director of Alumni Affairs.

References

Abdou, M, Musabanganji, E & Musahara, H, 2021. Tourism Demand Modelling and Forecasting: A Review of Literature. African Journal of Hospitality, Tourism and Leisure, vol. 10, no. 4, pp. 1370-1393. https://doi.org/10.46222/ajhtl.19770720-168

Abellana D, Rivero D, Aparente ME & Rivero, R, 2021. Hybrid SVR-SARIMA model for tourism forecasting using PROMETHEE II as a selection methodology: a Philippine scenario. Journal of Tourism Futures, vol. 7, no. 1. http://dx.doi.org/10.1108/JTF-07-2019-0070

Abing, AG, 2024. Exploring Tourists' Perspective on Environmental Fees in The Island Garden City of Samal. International Journal of Progressive Research in Engineering Management and Science (IJPREMS), vol. 4, no. 6, pp: 173-176. Retrieved from https://www.ijprems.com/uploadedfiles/paper//issue_6_june_2024/34750/final/fin_ijprems1717605288.pdf

Agada, IO, Eweh, EJ & Aondoakaa, SI, 2021. Time series ARIMA model for predicting monthly net radiation. Fudma Journal of Sciences, vol. 5, no. 4, pp.182-193. https://doi.org/10.33003/fjs-2021-0504-805

Almeida, A, Brás, S, Oliveira, I & Sargento, S, 2022. Vehicular traffic flow prediction using deployed traffic counters in a city. Future Gener. Comput. Syst. 2022, vol. 128, pp. 429–442. http://dx.doi.org/10.1016/j.future.2021.10.022

Andulana, DD, Calijan, MT & Albina, AC, 2021. Challenges and Opportunities in Philippine Tourism amid the COVID-19 Pandemic, December 2021. http://dx.doi.org/10.32871/rmrj.2109.02.08

Angelaccio, M, 2019. Forecasting Public Electricity Consumption with ARIMA Model: A Case Study from Italian Municipalities Energy Data, 2019. International

Symposium on Advanced Electrical and Communication Technologies (ISAECT), 1-3. Retrieved from https://ieeexplore.ieee.org/document/9069696

Anisa, MP, Irawan, H & Widiyanesti, S, 2021. Forecasting demand factors of tourist arrivals in Indonesia's tourism industry using recurrent neural network. IOP Conf. Series: Materials Science and Engineering 1077 (2021) 012035 IOP Publishing. http://dx.doi.org/10.1088/1757-899X/1077/1/012035

Anu, A, Gautam, N, Gautam, PK, Singh, J, Sharma, S, Kaushik, A & Obaid, AJ, 2022. Impact of post-COVID-19 on the hospitality tourism: Impact evaluation, survive, revive and thrive. International Journal of Health Sciences, vol. 6(S2), pp. 7152–7172. https://doi.org/10.53730/ijhs.v6nS2.6780

Arowosafe, FC, Akinwotu, O, Tunde-Ajayi, OA, Omosehin, OO & Osabuohien, ES, 2021. Push and pull motivation factors: a panacea for tourism development challenges in Oluminrin waterfalls, Nigeria. Journal of Policy Research in Tourism, Leisure and Events, vol. 14, pp. 63 – 74. http://dx.doi.org/10.1080/19407963.2021.2017729

Atasoy, E, Kabıyev, Y, Alıaskarov, DT & Kaimuldinova, Kvd, 2022. The South Tourism Regions of the Island of Mindanao from the Perspective of Tourism Geography. Uluslararası Yönetim Akademisi Dergisi, vol. 5, no. 2, pp. 267-293. https://doi.org/10.33712/mana.1147467

Bakar, NA & Rosbi, S, 2020. Effect of Coronavirus disease (COVID-19) to tourism industry. International Journal of Advanced Engineering Research and Science, vol. 7, no. 4, pp. 189–193. https://doi.org/10.22161/ijaers.74.23

Bartik, AW, Bertrand, M, Cullen, Z, Glaeser, E, Luca, M & Stanton, C, 2020. The impact of COVID-19 on small business outcomes and expectations. Proceedings of the National Academy of Sciences 117: 17656–66. https://doi.org/10.1073/pnas.2006991117

Bespalova, OG, 2022. Modeling and Forecasting Monthly Tourism Arrivals Since the COVID-19 Pandemic: Aruba Case. IMF Working Papers 2022/226, International Monetary Fund. Retrieved January 14, 2023, from https://www.imf.org/en/Publications/WP/Issues/2022/11/11/Modeling-and-Forecasting-Monthly-Tourism-Arrivals-to-Aruba-Since-COVID-19-Pandemic-525638

Bhowmik, D, 2020. Trends, Cycles and Seasonal Variations of Ukrainian Gross Domestic Product. Financial Markets, Institutions and Risks, vol. 4, no. 3, pp. 80-94. http://dx.doi.org/10.21272/fmir.4(3).80-94.2020

Bi, JW, Liu, Y & Li, H, 2020. Daily tourism volume forecasting for tourist attractions. Annals of Tourism Research, vol. 83. Retrieved July 16, 2024, from https://doi.org/10.1016/j.annals.2020.102923

Botero, CM, Cabrera, JA, Mercadé, S, Bombana, B, 2020. Análisis general y recomendaciones para afrontar la crisis de la COVID-19 en el turismo de sol y playa, In El Turismo de sol y Playa en el Contexto de la COVID-19. Escenarios y Recomendaciones; Eds.; Red Iberoamericana Proplayas: Santa Marta, Colombia, 2020, pp. 10–31. Retrieved from https://ri.conicet.gov.ar/bitstream/handle/11336/140731/CONICET_Digital_Nro.3952a361-cd77-47e4-90a2-f5e173bdc959_A.pdf?sequence=2

Caynila, KA, Luna, K & Milla, SA, 2022. The Philippine Tourism Sector Amid the Pandemic: Developments and Prospects. Economic Newsletter, no. 22-02. Retrieved June 18, 2023, from https://www.bsp.gov.ph/Media_And_Research/Publications/EN22-02.pdf

Centeno, R & Marquez, J, 2020. *How much did the Tourism Industry Lost? Estimating Earning Loss of Tourism in the Philippines*, Retrieved February 12, 2023, from https://arxiv.org/abs/2004.09952

Chipumuro, M & Chikobvu, D, 2022. Modelling Tourist Arrivals in South Africa To Assess the Impact of the COVID-19 Pandemic on the Tourism Sector. African Journal of Hospitality, Tourism and Leisure, vol. 11, no. 4, pp. 1381-1394. https://doi.org/10.46222/ajhtl.19770720.297

Cordero, T, 2021. *Foreign tourist arrivals in Philippines plunge 83.7% in 2020, amid COVID-19 pandemic.* GMA News Online. Retrieved February 04, 2023, from https://www.gmanetwork.com/news/money/economy/771410/foreign-touristarrivals-in-philippines-plunge-83-7-in-2020-amid-covid-19-pandemic/story/

Çuhadar, M, 2020. Modelling and forecasting inbound tourism demand to Croatia using artificial neural networks: a comparative study. Journal of Tourism and Services, vol. 11, no. 21, pp. 55-70. https://doi.org/10.29036/jots.v11i21.171

Dalagan, AM & Sy, Jr M, 2023. Post-Pandemic Business Recovery Experiences of Samal Island Beach Resorts Owners: A Hermeneutic Phenomenological Inquiry. International Journal of Research and Innovation in Social Science, pp. 475-491. Retrieved September 11, 2024, from https://dx.doi.org/10.47772/IJRISS.2023.7012040

Dann, GMS, 1977. Anomie, Ego-Enhancement and Tourism. Annals of Tourism Research, vol. 4, no. 4, pp. 184-194. https://doi.org/10.1016/0160-7383(77)90037-8

Department of Tourism, 2019. *Philippine Tourism Statistics*, PowerPoint Presentation, March 2020, Butuan City, Philippines. Retrieved February 22, 2023, from http://www.tourism.gov.ph/industry_performance/Dissemination_forum/2019_Tourism_Industry_Report.pdf

Diunugala, HP & Mombeuil, C, 2020. Modeling and predicting foreign tourist arrivals to Sri Lanka: A comparison of three different methods. Journal of Tourism, Heritage & Services Marketing, vol. 6, is. 3, pp. 3-13. http://doi.org/10.5281/zenodo.4055960.

Doğan, B, Ghosh, S, Tiwari, AK & Abakah, EJ, 2022. The effect of global volatility, uncertainty and geopolitical risk factors on international tourist arrivals in Asia. International Journal of Tourism Research, vol. 25, no. 1, pp. 1-62. Retrieved September 04, 2024, from https://doi.org/10.1002/jtr.2550

Eleni, S, 2020. Forecasting tourism demand in Greece by using Time-series. Retrieved January 06, 2023, from https://repository.ihu.edu.gr/xmlui/bitstream/handle/11544/29915/Forecasting20Tourism%20Demand%20In%20Greece_Saltsidou.pdf?sequence=1

Esquivas, MA, Sugiharti, L, Rohmawati, H & Sethi, N, 2021. Impacts and implications of a pandemic on tourism demand in Indonesia. Economics and Sociology, vol. 14, no. 4, pp. 133-150. http://dx.doi.org/10.14254/2071-789X.2021/14-4/8

Ete, AA, Suhartono, R & Atok, M, 2020. SSA and ARIMA for Forecasting Number of Foreign Visitor Arrivals to Indonesia. INFERENSI, vol. 3, no. 1. Retrieved June 22, 2024, from https://www.semanticscholar.org/paper/SSA-and-ARIMA-for-Forecasting-Number-of-Foreign-to-Ete-Suhartono/9f47484efd8677592c1ef1eb44c8d947122eec48

European Chamber of Commerce of the Philippines (ECCP), 2022. The Future of Tourism: Exploring the Glamour of Samal Island. Retrieved March 06, 2023, from https://www.eccp.com/events/1216#:~:text=As%20a%20response%2C%20the%20European,to%20discuss%20the%20awaiting%20opportunities

Fatima, N, Alamgir, A & Khan, MA, 2022. Rainfall forecast using SARIMA model along the coastal areas of Sindh Province. International Journal of Economic and Environmental Geology, vol. 13, no. 4, pp. 35-41. http://dx.doi.org/10.46660/ijeeg.v13i4.51

Gaetano, P, 2022. Using the SARIMA Model to Forecast the Fourth Global Wave of Cumulative Deaths from COVID-19: Evidence from 12 Hard-Hit Big Countries. Econometrics, vol. 10, no. 18. https://doi.org/10.3390/econometrics10020018

Ghalehkhondabi, I, Ardjmand, E, Young, WA & Weckman, GR, 2019. A review of demand forecasting models and methodological developments within tourism and passenger transportation industry. Journal of Tourism Futures, vol. 5, no. 1, pp. 75-93. https://doi.org/10.1108/JTF-10-2018-0061

Gössling, S, Scott, D & Hall, CM, 2021. Pandemics, tourism and global change: A rapid assessment of COVID-19. J. Sustain. Tour., pp. 1–20. Retrieved from https://portal.research.lu.se/en/publications/pandemics-tourism-and-global-change-a-rapid-assessment-of-covid-1

Goumas, S & Kontakos, S, 2021. Modeling and Forecasting of Tourist Arrivals in Crete Using Statistical Models and Models of Computational Intelligence: A Comparative Study. International Journal of Operations Research and Information Systems, vol. 12, no. 1. http://dx.doi.org/10.4018/IJORIS.2021010105

Gričar, S, 2023. Tourism Forecasting of "Unpredictable" Future Shocks: A Literature Review by the PRISMA Model. Journal of Risk and Financial Management, vol. 16, no. 493. http://dx.doi.org/10.3390/jrfm16120493

Gričar, S, Šugar, V & Baldigara, T, 2022. Some considerations about tourist arrivals and the COVID-19 pandemic – evidence from Slovenia and Croatia. Economic Research-Ekonomska Istraživanja. Retrieved March 12, 2023, from DOI: 10.1080/1331677X.2022.2053781. https://doi.org/10.1080/1331677X.2022.2053781

Guleria, S, 2019. Rationale of Push and Pull Theory Through IT in Tourist Motivations and Destination Attributes: A Case Study of Mcleodganj (HP) As Tourist

Destination. Proceedings of 10th International Conference on Digital Strategies for Organizational Success, pp. 921-934. https://dx.doi.org/10.2139/ssrn.3317772

Haryanto, T, 2020. COVID-19 pandemic and international tourism demand. JDE (Journal of Developing Economies), vol. 5, pp. 1–5. Retrieved from https://e-journal.unair.ac.id/JDE/article/download/19767/10766/74189

Hassouna, F & Al-Sahili, K, 2020. Practical Minimum Sample Size for Road Crash Time-Series Prediction Models. Advances in Civil Engineering, vol. 2020. Retrieved March 12, 2023, from https://doi.org/10.1155/2020/6672612

Höpken, W, Eberle, T, Fuchs, M, & Lexhagen, M, 2021. Improving Tourist Arrival Prediction: A Big Data and Artificial Neural Network Approach. Journal of Travel Research, vol. 60, no. 5, pp. 998-1017. Retrieved March 02, 2023, from https://doi.org/10.1177/0047287520921244

Hossen, SM, Ismail, TM, Tabash, MI & Abousamak, A, 2021. Accrued Forecasting On Tourist's Arrival in Bangladesh for Sustainable Development. GeoJournal of Tourism and Geosites, vol. 36(2spl), pp. 708–714. https://doi.org/10.30892/gtg.362spl19-701

Hu, H, Yang, Y & Zhang, J, 2021. Avoiding panic during pandemics: COVID-19 and tourism-related businesses. Tourism Management, vol. 86. Retrieved from https://doi.org/10.1016/j.tourman.2021.104316

Hussain, JN, 2021. Using Transformations to Predict and Smooth Time Series. Turkish Journal of Computer and Mathematics Education (TURCOMAT), vol. 12, no. 4, pp. 647-653. Retrieved from https://turcomat.org/index.php/turkbilmat/article/view/548

Huynh, DV, Truong, TTK, Duong, LH, Nguyen, NT, Dao, GVH & Dao, CN, 2021. The COVID-19 Pandemic and Its Impacts on Tourism Business in a Developing City: Insight from Vietnam. Economies, vol. 9, no. 4, p. 172. https://doi.org/10.3390/economies9040172

Ilmayasinta, N, 2021. Peramalan Kedatangan Wisatawan Asing Menggunakan Seasonal Arima Box-Jenkins. Barekeng: J. Il. Mat. & Ter., vol. 15, no. 02, pp. 223-230, June 2021. https://doi.org/10.30598/barekengvol15iss2pp223-230

Imam, A, 2020. Investigation of Parameter Behaviors in Stationarity of Autoregressive and Moving Average Models through Simulations. Asian Journal of Mathematical Sciences 4(4). https://doi.org/10.22377/ajms.v4i4.295

Sciences, vol. 4, is. 4 International Trade Centre, 2020. SME Competitiveness Outlook 2020: Covid-19: Great Lockdown and its Impact on Small Business. ITC, Geneva. Retrieved from http://www.intracen.org/SMEOutlook/

Jackson, EA & Tamuke, E, 2019. Predicting disaggregated tourist arrivals in Sierra Leone using ARIMA model. Theoretical and Practical Research in Economic Fields, vol. 10, no. 2, pp.132-142. https://doi.org/10.14505/tpref.v10.2(20).06

Jaffur, ZK, Tandrayen-Ragoobur, V, Seetanah, B & Gopy-Ramdhany, N, 2022. Impact of COVID-19 on a tourist-dependent economy and policy responses: the case of

Mauritius. Journal of Policy Research in Tourism, Leisure and Events. http://dx.doi.org/10.1080/19407963.2022.2113090

Jamal, NF, Abdul Ghafar, NM, Chek, MZA & Ismail, IL, 2019. Research of Forecasting on Tourist Arrivals to Malaysia. International Journal of Innovative Technology and Exploring Engineering (IJITEE), vol. 8, no. 12, pp. 686-689. Retrieved from https://www.ijitee.org/wp-content/uploads/papers/v8i12S2/L111910812S219.pdf

Jaya, GN & Sunengsih, N, 2022. Forecasting For the Arrival of International Tourists After Two Years of The Covid-19 Pandemic in Indonesia. International Journal of Applied Research in Social Sciences, vol. 4, no. 1, pp. 1-8. https://doi.org/10.51594/ijarss.v4i1.297

Johar, K, Tan, D, Maung, Y & Douglas, I, 2022. Destination Marketing: Optimizing Resource Allocation Using Modern Portfolio Theory. Journal of Travel Research, vol. 61, no. 6, pp. 1358-1377. https://doi.org/10.1177/00472875211025099

Juznik Rotar, L, Kontosic Pamic, R & Bojnec, S, 2019. Contributions of small and medium enterprises to employment in the European Union countries. Economic Research-Ekonomska Istrazivanja, vol. 32, no. 1, pp. 3302–3314. https://doi.org/10.1080/1331677X.2019.1658532

Kaewmanee, P, Muangprathub, J & Sae-jie, W, 2021. Forecasting Tourist Arrivals with Keyword Search using Time Series. 2021 18th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON), pp. 171-174. https://doi.org/10.1109/ECTI-CON51831.2021.9454824

Ke, W, 2024. Tourism Demand Forecast and Future Market Trend Research. Advances in Politics and Economics, vol. 7, no. 2, pp. 202-210. http://dx.doi.org/10.22158/ape.v7n2p202

Khan, A, Bibi, S, Lorenzo, A, Lyu, J & Babar, ZU, 2020. Tourism and Development in Developing Economies: A Policy Implication Perspective. Sustainability 2020, vol. 12, no. 1618. https://doi.org/10.3390/su12041618

Kiran, N & Reddy, M, 2022. Forecasting Analysis of International Tourist Arrivals to Hyderabad, India, Using ARIMA Model. Mathematical Statistician and Engineering Applications, vol. 71, no. 4, pp. 3801-3812. https://doi.org/10.17762/msea.v71i4.944

Kourentzes, N, Saayman, A, Jean-Pierre, P, Provenzano, D, Sahli, M, Seetaram, N & Volo, S, 2021. Visitor arrivals forecasts amid COVID-19: A Perspective from the Africa team. Annals of Tourism Research, vol. 88. https://doi.org/10.1016/j.annals.2021.103197

Kyriakaki, A, Stavrinoudis, T & Daskalopoulou, G, 2020. Investigating the Key Factors Influencing the International Tourists' Decision-Making on Choosing a Destination, *Springer Proceedings in Business and Economics*, pp. 335-352. Retrieved from https://www.researchgate.net/publication/338913720_Investigating_the_Key_Factors_Influencing_the_International_Tourists'_Decision-making_on_Choosing_a_Destination

Lakshmi, MM, Sandhyai, D & Rakesh, P, 2024. Supply Chain Management Enhance NG Efficiency and Collaboration Industry Company. International Research Journal on Advanced Engineering and Management (IRJAEM), vol. 2, no. 5, pp. 1762-1765. http://dx.doi.org/10.47392/IRJAEM.2024.0261

Law, R, Li, G, Fong, DKC & Han, X, 2019. Tourism demand forecasting: A deep learning approach. Annals of Tourism Research, vol. 75, pp. 410-423. https://doi.org/10.1016/j.annals.2019.01.014

Li, G & Wu, DC, 2019. Introduction to the special issue: Tourism forecasting – New trends and issues. Tourism Economics, vol. 25, no. 3, pp. 305–308. https://doi.org/10.1177/1354816618816809

Lin, S, 2023. Forecasting the trend of the tourism industry in the United States: using ARIMA model and ETS model. Highlights in Business, Economics and Management, vol. 10, pp. 111-121. Retrieved from http://dx.doi.org/10.54097/hbem.v10i.7964

Liu, A, Vici, L, Ramos, V, Giannoni, S & Blake, A, 2021. Visitor arrivals forecasts amid COVID-19: A perspective from the Europe team. Annals of Tourism Research, vol. 88. https://doi.org/10.1016/j.annals.2021.1031820160-7383

Makoni, T & Chikobvu, D, 2021. Modelling International Tourist Arrivals Volatility in Zimbabwe Using a GARCH Process. African Journal of Hospitality, Tourism and Leisure, vol. 10, no. 1, pp. 639-653. https://doi.org/10.46222/ajhtl.19770720-123

Makoni, T, Mazuruse, G & Nyagadza, B, 2023. International tourist arrivals modelling and forecasting: A case of Zimbabwe. Sustainable Technology and Entrepreneurship, vol. 2, no. 1. http://dx.doi.org/10.1016/j.stae.2022.100027

Malangalila, SR & Mhache, EP, 2023. The Role of Local Government in the Development of Tourism in Iringa Region, Tanzania. International Journal for Multidisciplinary Research, vol. 5, no. 5, pp. 1-13. http://dx.doi.org/10.1080/09709274.2013.11906553

Maliberan, R, 2019. Forecasting Tourist Arrival in the Province of Surigao del Sur, Philippines, using Time Series Analysis. International Journal on Informatics Visualization, vol. 3, no. 3. Retrieved from http://dx.doi.org/10.30630/joiv.3.3.268

Mammen, J, Alessandri, TM & Weiss, M, 2019. The risk implications of diversification: Integrating the effects of product and geographic diversification. Long Range Planning, vol. 54, no. 1. https://doi.org/10.1016/j.lrp.2019.101942

Michael, N, Nyadzayo, MW, Michael, I & Balasubramanian, S, 2020. Differential roles of push and pull factors on escape for travel: Personal and social identity perspectives. International Journal of Tourism Research, vol. 22, pp. 464-478. https://doi.org/10.1002/jtr.2349

Msofe, ZA & Mbago, MC, 2019. . Gen. Lett. Math. 2019, vol. 7, pp. 100– 107Forecasting international tourist arrivals in Zanzibar using Box–Jenkins SARIMA model. Retrieved from https://www.refaad.com/Files/GLM/7-2-6.pdf

Murodova, N, 2024. Tourism Pricing Strategies. European International Journal of Multidisciplinary Research and Management Studies, vol. 4, no. 4, pp. 216-222. Retrieved from https://www.eipublication.com/index.php/eijmrms/article/view/1762

Mursalina, R, Masbar & Suriani, 2022. Impact of Covid-19 Pandemic on Economic Growth of the Tourism Sector in Indonesia. International Journal of Quantitative Research and Modeling, vol. 3, no. 1, pp. 18-28. Retrieved April 08, 2023, from https://journal.rescollacomm.com/index.php/ijqrm/index

Nagendrakumar, N, Lokeswara, AA, Gunawardena, SADCK, Kodikara, UP, Rajapaksha, RWNH & Ratnayake, KRMCS, 2021. Modeling and forecasting tourist arrivals in Sri Lanka. SLIIT Business Review, vol. 1, no. 2, pp. 95-120. https://doi.org/10.54389/GKED9337

Nguyen, KT, 2020. Safety Plan during Covid-19 Pandemic in Restaurant Industry: Case Study: KOKORO Sushi. Vantaa: Laurea University, pp. 1-39. Retrieved from https://www.theseus.fi/bitstream/handle/10024/354657/Nguyen_Thanh.pdf?sequence=2

Nikitenko, K, 2024. The Specifics of Tourism Business Management in The Conditions of Global Instability. Actual Problems of Economics, vol. 1, no. 275, pp. 34-40

Nwokike, CC, Offorha, BC, Maxwell, O, Uche-Ikonne, O & Onwuegbulam, CC, 2020. ARIMA Modelling of Neonatal Mortality in Abia State of Nigeria. Asian Journal of Probability and Statistics, vol. 6, no. 2, pp. 54-62. https://doi.org/10.9734/ajpas/2020/v6i230158

Nyagadza, B & Chigora, F, 2022. Futurology of ethical tourism digital & social media marketing post-COVID-19, In A. Sharma, A. Hassan, P. Mohanty (Eds.), Chapter 6 in COVID-19 and Tourism Sustainability: Ethics, Responsibilities, Challenges and New Directions Eds. Routledge, Taylor & Francis, Abingdon, United Kingdom (UK). Retrieved from https://www.routledge.com/COVID-19-and-the-Tourism-Industry-Sustainability-Resilience-and-New-Directions/Sharma-Hassan-Mohanty/p/book/9781032075129

OECD, 2020. Tourism Policy Responses to the coronavirus (COVID-19). Retrieved January 20, 2023. from https://www.oecd.org/coronavirus/policy-responses/tourism-policyresponses-to-the-coronavirus-covid-19-6466aa20/

Polintan SN, Cabauatan LL, Nepomuceno JP, Mabborang RC & Lagos JC, 2023. Forecasting Gross Domestic Product in the Philippines Using Autoregressive Integrated Moving Average (ARIMA) Model. European Journal of Computer Science and Information Technology, vol.11, no.2, pp.100-124. Retrieved from https://doi.org/10.37745/ejcsit.2013/vol11n2100124

Prastyadewi, MI, Tantra, IGLP & Pramandari, PY, 2023. Digitization and Prediction of The Number of Tourist Visits in The Bali Province. Jurnal Ekonomi dan Bisnis Jagaditha, vol. 10, no. 1, pp. 89-97. http://dx.doi.org/10.22225/jj.10.1.2023.89-97

PricewaterhouseCoopers (PWC), 2020. Impact of COVID-19 on the Philippine tourism industry. Retrieved November 18, 2020, from https://www.pwc.com/ph/en/publications/tourism-pwc-philippines/tourism-covid-19.html

Priyadarshini, E, Preethi, ES, Vidhya, M, Chakkravarthi, S & Govindarajan, A, 2022. Modeling and forecasting using auto-regressive integrated moving average. 2nd

International Conference on Mathematical Techniques and Applications: ICMTA2021. http://dx.doi.org/10.1063/5.0108756

Rodrı´guez, RP & Gallego, MS, 2020. Modelling tourism receipts and associated risks using long-range dependence models. Tourism Economics 2020, vol. 26, no. 1, pp. 70–96. https://doi.org/10.1177/1354816619828170

Rosli, S & Jamil, N, 2020. Conceptual Framework Related to The Impact of Coronavirus Disease 2019 (Covid-19) on Malaysian Private Entity Reporting Standard (MPERS) Adoption by Small and Medium Enterprises (SMES) In Malaysia. Penang: Universiti Sains Islam Malaysia. https://doi.org/10.33102/uij.vol33noS4.413

Ruiz Reina, MÁ, 2021. Entropy Method for Decision-Making: Uncertainty Cycles in Tourism Demand. Entropy 2021, vol. 23, no. 1370. https://doi.org/10.3390/e23111370

Ryan, O, Haslbeck, J & Waldorp, L, 2023. Non-Stationarity in Time-Series Analysis: Modeling Stochastic and Deterministic Trends. Retrieved February 20, 2024, from: https://osf.io/z7ja2/download

Sadhale, M & Sathe, S, 2020. A Study of Push and Pull Factors Influencing Travel Preferences of Gen X Travelers from Pune City. International Journal of Disaster Recovery and Business Continuity, vol.11, no. 1, pp. 536-551. Retrieved from http://sersc.org/journals/index.php/IJDRBC/article/view/7501

Santamaria, ER, 2020. Sustainable Local Tourism Industry in BLOM Areas. International Association of Scholarly Publishers, Editors and Reviewers, Inc., vol. 20. Retrieved from https://aseanresearch.org/downloads/iasper/publication/13/4_EDRICK%20RAY%20S%20SANTAMARIA.pdf

Segal, UA, 2019. Globalization, migration, and ethnicity. Public health, vol. 172, pp. 135-142. https://doi.org/10.1016/j.puhe.2019.04.011

Šenková, A, Košíková, M, Matušíková, D, Šambronská, K, Kravˇcáková Vozárová, I & Kotuliˇc, R, 2021. Time Series Modeling Analysis of the Development and Impact of the COVID-19 Pandemic on Spa Tourism in Slovakia. Sustainability 2021, vol. 13, no. 11476. https://doi.org/10.3390/su132011476

Serrona, KRB, Yu, J & Camarin, MJA, 2022. Addressing Marine Litter through Sustainable Tourism: The Case of the Siargao Islands in the Southern Philippines, ADBI Working Paper 1302, Tokyo: Asian Development Bank Institute. Retrieved March 15, 2023, from https://www.adb.org/publications/addressing-marine-litter-through-sustainable-tourism-thecase-of-the-siargao-islands-in-the-southern-philippines

Sigala, M, 2020. Tourism and COVID-19: Impacts and implications for advancing and resetting industry and research. Journal of Business Research (2020), vol. 117, pp. 312-321. Retrieved from http://dx.doi.org/10.1016/j.jbusres.2020.06.015

Song, H, Qiu, R & Park, J, 2019. A review of research on tourism demand forecasting: launching the annals of tourism research curated collection on tourism demand forecasting. Annals of Tourism Research, vol. 75, pp. 338-362. https://doi.org/10.1016/j.annals.2018.12.001

Sonobe, TA, Takeda, S, Yoshida & HT Truong, 2021. The Impacts of the COVID-19 Pandemic on Micro, Small, and Medium Enterprises in Asia and Their Digitalization Responses. ADBI Working Paper 1241, Tokyo: Asian Development Bank Institute. Retrieved January 13, 2023, from https://www.adb.org/publications/impacts-covid-19-pandemic-msme-asia-their-digitalizationresponses

Subramaniam, G & Muthukumar, I, 2020. Efficacy of time series forecasting (ARIMA) in post-COVID econometric analysis. International Journal of Statistics and Applied Mathematics, vol 5, no. 6, pp. 20-27. http://dx.doi.org/10.22271/maths.2020.v5.i6a.609

Tan, CV, Singh, S, Lai, CH, Zamri, ASSM, Dass, SC, Aris, TB, Ibrahim, HM & Gill, BS, 2022. Forecasting COVID-19 Case Trends Using SARIMA Models during the Third Wave of COVID-19 in Malaysia. Int. J. Environ. Res. Public Health 2022, vol. 19, no. 1504. https://doi.org/10.3390/ijerph19031504

Tharu, NK, 2019. Forecasting International Tourists Arrival in Nepal: An Application of ARIMA. Department of Statistics. Retrieved May 06, 2023, from https://www.researchgate.net/publication/342354362

Thushara SC, Su, J & Bandara JS, 2019. Forecasting international tourist arrivals in formulating tourism strategies and planning: The case of Sri Lanka. Cogent Economics & Finance (2019), 7:1699884. https://doi.org/10.1080/23322039.2019.1699884

Turtureanu, AG, Pripoaie, R, Cretu, CM, Sirbu, CG, Marinescu, ES, Talaghir, LG & Chit, F, 2022. A Projection Approach of Tourist Circulation under Conditions of Uncertainty. Sustainability 2022, vol. 14, no. 1964. https://doi.org/10.3390/su14041964

Upadhayaya, RP, 2021. Forecasting International Tourists Arrival to Nepal Using Autoregressive Integrated Moving Average (ARIMA). Janapriya Journal of Interdisciplinary Studies, vol. 10, no. 01, pp.107-117. Retrieved from https://www.nepjol.info/index.php/JJIS/article/view/42614/32450

Velos, SP, Go, MB, Bate, GP & Joyohoy, EB, 2020. A Seasonal Autoregressive Integrated Moving Average (SARIMA) Model to Forecasting Tourist Arrival in the Philippines: A Case Study in Moalboal, Cebu (Philippines). Recoletos Multidiscipline Res J., vol. 8, no. 1, pp. 67–78. Retrieved from https://doi.org/10.32871/rmrj2008.01.05

Velu, SR, Ravi, V & Tabianan, K, 2022. Predictive analytics of COVID 19 cases and tourist arrivals in ASEAN based on covid 19 cases. Health and Technology, vol. 12, pp. 1237–1258. Retrieved June 02, 2023, from https://doi.org/10.1007/s12553-022-00701-7

Waluyo, JE, 2019. Peramalan Kedatangan Wisatawan Manca Negara Melalui Bandara Husein Sastra Negara Bandung Dengan Menggunakan Metode Arima

(Autoregressive Integrated Moving Average). Jurnal Kepariwisataan: Destinasi, Hospitalitas dan Perjalanan. https://doi.org/10.34013/jk.v3i1.32

Wen, J, Wang, W, Kozak, M, Liu, X & Hou, H, 2020. Many brains are better than one: The importance of interdisciplinary studies on COVID-19 in and beyond tourism. Tour. Recreat. Res. 2020, p. 1–4. https://doi.org/10.1080/02508281.2020.1761120

Wieprow, J & Gawlik, A, 2021. The Use of Discriminant Analysis to Assess the Risk of Bankruptcy of Wen Enterprises in Crisis Conditions Using the Example of the Tourism Sector in Poland. Risks, vol. 9, p. 78. https://doi.org/10.3390/risks9040078

Williams, AM, Rodríguez Sánchez, I & Škokić, V 2021, Innovation, risk, and uncertainty: A study of tourism entrepreneurs, *Journal of Travel Research*, vol. 60, no. 2, pp. 293-311. https://doi.org/10.1177/0047287519896012

Wu, DCW, Ji, L, He, K & Tso, KFG, 2021. Forecasting Tourist Daily Arrivals with A Hybrid Sarima– Lstm Approach. Journal of Hospitality & Tourism Research, vol. 45, no. 1, pp. 52–67. https://doi.org/10.1177/1096348020934046

Yang, R, Liu, K, Su, C, Takeda, S, Zhang, J & Liu, S, 2023. Quantitative Analysis of Seasonality and the Impact of COVID-19 on Tourists' Use of Urban Green Space in Okinawa: An ARIMA Modeling Approach Using Web Review Data. Land 2023, vol. 12, no. 1075. https://doi.org/10.3390/land12051075

Yap, DJ, 2020. Duterte Hit for Delay of Bayanihan 2. Philippine Daily Inquirer, 5 September 2020. Retrieved January 13, 2023, from https://newsinfo.inquirer.net/1331449/duterte- hit-for-delay-of-bayanihan-2

Yollanda, M & Devianto, D, 2020. Hybrid model of seasonal ARIMA-ANN to forecast tourist arrivals through Minangkabau International Airport. In Proceedings of the 1st International Conference on Statistics and Analytics, ICSA 2019, 2-3 August 2019, Bogor, Indonesia. Retrieved from https://eudl.eu/doi/10.4108/eai.2-8-2019.2290473

Zhang, B, 2022. Based on HP-ARIMA Method Automotive Industry Stock Net Value Valuation Analysis-Taking 10,908 samples from 9 enterprises as examples. *2022 6th International Conference on Education, Management and Social Science (EMSS 2022),* pp. 72-76. Retrieved February 15, 2024, from https://www.clausiuspress.com/conferences/AETP/EMSS%202022/ES013.pdf

Zhang, Y, Choo, WC, Ho, JS & Wan, CK, 2022. Single or Combine? Tourism Demand Volatility Forecasting with Exponential Weighting and Smooth Transition Combining Methods. Computation 2022, vol. 10, no. 137. https://doi.org/10.3390/computation10080137

Zielinski, S & Botero, C, 2020. Beach Tourism in Times of COVID-19 Pandemic: Critical Issues, Knowledge Gaps and Research Opportunities. Int. J. Environ. Res. Public Health 2020, vol. 17, p.7288. https://doi.org/10.3390/ijerph17197288

Zlatkou, P, 2021. Prediction of Tourism Demand in Greece Using Time Series. A thesis submitted for the degree of Master of Science (MSc) in Data Science, pp. 1-28. Retrieved March 05, 2024, from: https://repository.ihu.edu.gr/xmlui/bitstream/handle/11544/29762/New%20-

PREDICTION%20OF%20TOURISM%20DEMAND%20IN%20GREECE%20USING%20TIME%20SERIES%20FORECASTING.pdf