FORECASTING TOURIST ARRIVALS IN MATI CITY USING SEASONAL AUTOREGRESSIVE INTEGRATED MOVING AVERAGE (SARIMA).

Abstract of thesis:

This study forecasted monthly tourist arrivals in Mati City, Davao Oriental to support evidence-based tourism planning and management. Using a quantitative time-series research design, monthly tourist arrival data from January 2013 to December 2023 were analyzed using the Seasonal Autoregressive Integrated Moving Average (SARIMA) model following the Box–Jenkins methodology. Results revealed strong and consistent seasonality, with peak tourist arrivals occurring during April, May, and December, and lower arrivals during August and September. The best-fit SARIMA (1,1,3)(0,0,2)[12] model demonstrated satisfactory diagnostic results, including white-noise residuals and low information criteria values, indicating good model adequacy and forecasting reliability. Forecasts suggested that tourist arrivals in Mati City would stabilize at approximately 35,000 visitors per month, signifying that the tourism sector has reached a relatively steady phase under current conditions. The study concluded that while tourism demand in Mati City is predictable and strongly seasonal, sustained growth requires strategic interventions beyond existing trends. The findings contribute to tourism forecasting literature and provide practical insights for local government units and tourism stakeholders in improving resource allocation and sustainable tourism development.

Thesis Chapters:

1. Introduction

Tourism in every country plays an important role in socio-economic development, particularly in regions with natural and cultural wealth, such as the Philippines' Davao region. It significantly contributed to local economies by generating employment opportunities within the community, while encouraging the creation of businesses and investments. The region, including Mati City, offers various attractions and highlights, such as coastal views and vibrant cultural celebrations. Despite the strength and variation in tourist influx, operational challenges persist, making it difficult to sustain growth and development. Zhange, Song, and Wen (2020) noted that forecasting limitations often arise from inadequate accommodation capacity, insufficient recreational infrastructure, underdeveloped or inconsistent supply chains, and limited transportation infrastructure, all of which hinder accurate demand forecasting. Even in the studies by Kuscer, Eichelberger, and Peters (2022), which highlighted the importance of understanding tourists' behavior, there should be a management strategy to address challenges effectively.

In the Philippine context, the national Tourism Plan considers tourism to be a national economic priority (Gasga, 2022; Yamagisgi, Gantalao& Ocampo, 2024). The plan must be integrated with technology and data analytics into tourism planning and operations to ensure efficiency and competitiveness (Leong, Leong, & Leong, 2024). However, in existing approaches to forecasting tourist arrivals, some rely on conventional methods that lack accuracy and adaptability to local conditions. While various urban destinations such as Davao City and Cebu have been widely examined in tourism research, smaller but developing destinations like Mati City must receive greater attention; likewise, this city receives only limited attention. The imbalance restricts stakeholders' capacity to realize tourism's greater potential, particularly in areas with strong growth forecasts; however, it also limits the availability of planning tools. Including the issue during the COVID-19 pandemic, which decreased the number of tourists due to international border closures, travel restrictions, quarantine measures, and the UNWTO-imposed limitation on domestic travel (Tourism Academy, 2025). These address the gaps and support broader national objectives that promote sustainable and competitive tourism development.

Tourism forecasts are widely recognized as the best tool for effective resource allocation globally, even for marketing strategies and service delivery. As noted by Dimitriadou, Gogas, & Papadimitriou (2024) and Baldigara& Sugar (2021), accurate forecasts enable destinations to anticipate seasonal demand, respond to unexpected downturns, and even design long-term strategies that support sustainable growth. Nonetheless, many destinations continue to face shortcomings, like the absence of contingency or overflow accommodation systems, emergency lodging arrangements, homestay programs, or even temporary facilities. These challenges might lead to visitor dissatisfaction and negatively affect the destination's reputation. Despite the importance of tourism, demand forecasting also remains underexplored in the local area. The data-driven approaches identified opportunities to improve tourism management. The operational gap emphasizes the need to focus research that could support decision-making among stakeholders.

This study aligned with Sustainable Development Goal (SDG) 8, which focuses on industry, innovation, and infrastructure, by applying advanced forecasting strategies and data analytics, specifically the SARIMA model. To improve the tourism planning and infrastructure development. It also aligns with SDG 12 on responsible consumption and production by promoting sustainable tourism practices, efficient resource use, improved waste management, and enhanced energy efficiency.

This study is based on the theories of Butler's (1980) Tourist Area Life Cycle (TALC) and Box-Jenkins Time Series Analysis Framework (Box et al., 2015). Both these frameworks give a better perspective on tourism development and demand forecasting. The Butler's TALC model outlines how a tourism destination would develop, including exploration, involvement, development, consolidation, stagnation, and eventual decline or innovation. The framework offers a valuable perspective on how the tourist demand adapts alongside local conditions. This allows a strategist who understands the destination’s development direction. The TALC framework provided tourism forecasting within the broader context of Mati City's tourism cycle, aiding in identifying the current situation and envisioning the potential future destination.

Adding this perspective, the time-series analysis framework, as discussed by Duan (2024), poses a challenge for the statistical approach to modeling and forecasting time-dependent data. The SARIMA model, based on this framework, is suitable for forecasting tourism conditions, accounting for trends, seasonal variations, and random fluctuations. By combining this statistical method, this study generates data to forecast tourist arrivals in Mati City.

This study seeks to address the problem by developing a SARIMA model grounded in Mati City's specific perspective. The objectives are: to analyze the seasonal pattern in tourist influx; to generate a short-term forecast using the best-fit SARIMA model; and to provide practical recommendations for local tourism stakeholders by integrating the data with advanced forecasting techniques. This study is relevant to both academic and practical tourism management. This could contribute to decision-making in the tourism sector and to the present framework, which could be beneficial for similar regional conditions. The urgency underscores the importance of tourism in sustaining development in the Philippines.

These operational gaps faced by those handling tourism in Mati City highlight the potential benefits of enhanced forecasting capabilities for an emerging destination. Accurate demand forecasts guide workforce planning, marketing strategies, and even infrastructure investment, ensuring tourism growth remains sustainable and inclusive for everyone. Furthermore, this emphasizes data-driven decision making, strength, resilience, and adaptability in facing any condition, which could enhance competitiveness.

2. Method

Dataset

The dataset used in this study comprised monthly historical records of tourist arrivals in Mati City, Davao Oriental, spanning January 2013 to December 2023. These records were sourced from the Department of Tourism, Region XI, and the City of Mati's Local Government Unit Tourism Operations Department. This dataset included monthly tourist arrival figures, categorized by domestic and international visitors, and accounted for seasonal variations, including peak and off-peak periods. To ensure the data is reliable, a cross-verification with official reports was conducted. This dataset provided the foundational input for the SARIMA modeling process to forecast seasonal patterns and long-term trends in tourist arrivals.

Study Locale

The focus of this study is on the province of Davao Oriental, Philippines, particularly in Mati City. Since Mati City is home to prominent and breathtaking natural attractions, including Dahican Beach and Pujada Bay, it is one of the rising tourism hubs in the Davao Region. The vibrant tourism sector significantly contributes to the local economy and necessitates accurate forecasting of tourist arrivals for effective planning and resource allocation. The seasonal influx of tourism, influenced by local events and holidays, makes it an ideal case for examining advanced forecasting methodologies. This study uses documented tourist arrival data from 2013 to 2023, including the pre-pandemic and post-pandemic periods. This study focuses on the availability and trends of tourism infrastructure, such as accommodations, transportation systems, and excursion activities, as well as seasonal variation. Only documented and verifiable data from local tourism offices or recognized government sources were to be considered. The classification where such differentiation is available, and the study is expected to be completed in December 2025.

However, the study was limited by some factors. Firstly, during the COVID-19 pandemic, tourist activities resulted in no arrivals, which may alter the trend analysis and reduce forecasting accuracy. Then, the availability and consistency of tourism data, especially the separation between local and international data, but not the primary sources or the data collection methods.

The COVID-19 pandemic (2020–2022) caused severe disruptions in tourist arrivals, leading to a period of near-zero activity. So, these observations act as outliers in the time series. The SARIMA model, a univariate approach, incorporates these shocks within its stochastic error structure without explicitly modeling structural breaks. Despite this, the model remained vigorous, as evidenced by steady residual diagnostics. However, the unprecedented shocks might reduce forecast accuracy, which highlights the need for hybrid or intervention-based models for future research.

Design and Procedure

This study employed a quantitative research design utilizing time-series analysis to forecast tourist arrivals in Mati City. This procedure begins with the collection and preprocessing of historical monthly tourist arrival data to ensure fullness and consistency. A descriptive analysis was conducted to identify initial trends and seasonal patterns in the data. The dataset is divided into two sets: the training and validation sets, from January 2013 to December 2023, for model estimation, while data from January to December 2024 was reserved for validation.

The Seasonal Autoregressive Integrated Moving Average (SARIMA) model was developed using the Box-Jenkins methodology, which involves identifying the model's order, fitting it to the data, and diagnosing its adequacy through residual analysis. The final forecasts were validated by comparing predicted values with 2024 actual data to assess the model's predictive accuracy.

Statistical Tools

The primary statistical tool employed in this study is the Seasonal Autoregressive Integrated Moving Average (SARIMA) model. SARIMA is particularly suitable for time-series data that exhibit both trend and seasonal components. The estimation process follows the Box-Jenkins methodology, which consists of four steps:

First, time-series plots, autocorrelation, and partial autocorrelation functions were used to determine the model's seasonal and non-seasonal parameters *(p, d, q)* and *(P, D, Q).*

Second, identified parameters are estimated using maximum likelihood or other appropriate statistical techniques.

Third, the model's residuals were evaluated to ensure they were random and that no patterns remained unresolved. Diagnostic tests, such as the Ljung-Box test, were used to confirm the appropriateness of the model.

Lastly, whenforecasting, once validated, the SARIMA model was used to forecast monthly tourist arrivals for 2024, incorporating identified seasonal and non-seasonal components.

The Seasonal Autoregressive Integrated Moving Average (SARIMA) model extends the ARIMA model to incorporate seasonality, making it ideal for analyzing and forecasting data with periodic patterns, such as monthly tourist arrivals in Mati City. The general form of SARIMA is denoted as the SARIMA (p,d,q) $(P, D, Q)_s$, where p,d,q represents the orders of the non-seasonal autoregression (AR), differencing, and moving average (MA) components, and P, D, Q represent the seasonal counterparts, with the s as the seasonal period (e.g., $s = 12$ for monthly data). The SARIMA model can be expressed as:

- $$\Phi_P(B^s)\phi_p(B)(1-B)^d(1-B^s)^D Y_t \ = \ \Theta_Q(B^s)\theta_q(B)\epsilon_t,$$

where B is the backshift operator, then $(B^k Y_t = Y_{t-k})$, $\phi_p(B)$ and $\theta_q(B)$ are polynomials for the non-seasonal AR and MA terms, $\Phi_P(B^s)$ and $\Theta_Q(B^s)$ are polynomials for the seasonal AR and MA terms, while ϵt represents the white noise error term. In the Mati City context, the seasonal differencing $(1-B_s)^D$captured the annual patterns of tourist arrivals, while the non-seasonal differencing $(1-B)^d$ accounted for any long-term trends. The presence of both seasonal and non-seasonal components ensures that the SARIMA model accurately captures the fundamental dynamics of monthly tourist arrivals, providing forecasts that support strategic tourism management and planning. The SARIMA model's ability to account for seasonality and trends makes it a robust tool for generating actionable forecasts, enabling tourism stakeholders in Mati City to make informed decisions.

3. Results and Discussion

In Figure 1, the decomposition of the multiplicative time series for tourist arrivals in Mati City, in the first observed component or in the top panel, revealed that the recurring fluctuation indicated repeated peaks and troughs across time. This means that the characteristic of tourism patterns is driven by seasonality. The trend components or the second panel indicated a slow upward movement, which suggests a long-term increase in the overall tourist arrivals that aligns with the development of Mati's coastal tourism infrastructure and the increased of the domestic travel activity over the recent years.

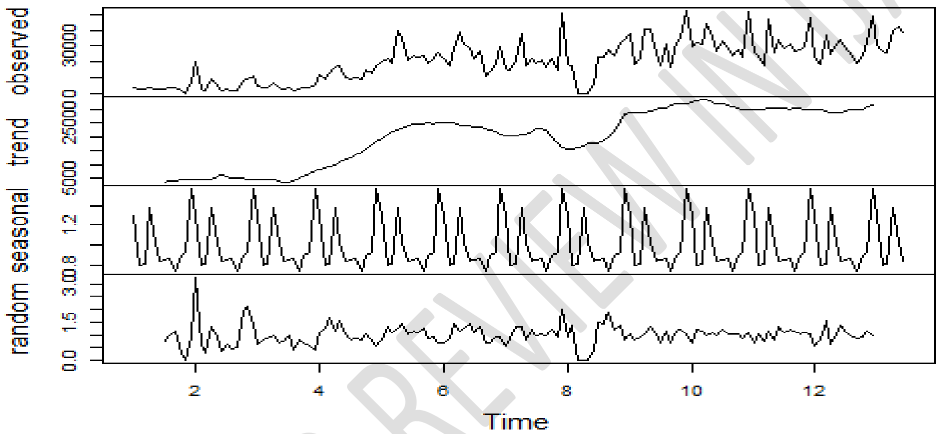

Figure 1. *Decomposition of the multiplicative time series for tourist arrivals in Mati City*

The seasonal component in the third panel demonstrated a strong and consistent annual sequence. This confirms that the tourist demand follows the predictable seasonal rhythm, this means that the peak happened during the months of April and May, within the summer months, and the Christmas holiday season in December. The random components or the last panel indicated fluctuations around zero with small spikes, indicating that the unsystematic shocks, such as the weather events or the policy changes, have limited and temporary effects. This decomposition validated that the time series is best modeled multiplicatively, as the trend and seasonal variation augment with the increasing tourist arrivals; this pattern shows consistency with the nonstationary tourism data (Hyndman &Athanasopoulus, 2022)

The estimated ARIMA parameters in Table 1 revealed that the both short-term autoregressive and seasonal moving average components, reflect a complex dynamic in monthly tourist arrivals. In the AR (1) coefficient got (−0.707), which is negative and large in magnitude; this means strong mean-reverting behavior, where a rise in arrivals during one month tends to be followed by a decline in the next. This oscillatory dynamic common in tourism demand, that influenced by alternating peak and off-peak seasons. Meanwhile, the positive SMA terms (SMA1 = 0.233, SMA2 = 0.136) this captured the persistent seasonal effects, meaning that shocks in a given tourism season tend to influence the future seasons in the same direction. Whereas, it is an important part of the multiple MA terms (MA2, MA3) shown that the past forecast errors still affecting the present predictions up to the three (3) periods ahead, indicating momentum in the tourism trend.

Table 1. *Model coefficients of the seasonal ARIMA model for tourist arrivals in Mati City*

Parameter	Estimate	SE
AR(1)	−0.707	0.1589
MA(1)	0.102	0.1759
MA(2)	−0.479	0.1241
MA(3)	−0.272	0.0827
SMA(1)	0.233	0.0872
SMA(2)	0.136	0.0753

Note. AR = autoregressive; MA = moving average; SMA = seasonal moving average.

In the view, this model structure suggested that the tourist arrivals influenced by the memory process in Mati City, not simply by abrupt past values, but this also through the seasonal periodicity related with the holidays, weather, and local events. These findings aligned with Hyndman and Athanasopoulos (2022), who emphasize that the seasonal ARIMA models effectively capture the cyclical tourism patterns where the visitor flows fluctuate predictably over the year.

In Table 2, the model got relatively low AIC (3113) and BIC (3134) values demonstrated model reach the strong trade-off between accuracy and parsimony. These indices are crucial in evaluating model appropriateness. This means that the lower values typically mean is better predictive performance relative to competing specifications, and the minor difference of 1 point between the AIC and AICc suggests that the model's sample size is adequate relative to the parameter count, minimizing overfitting risk. This confirms that the selected model likely represents the most efficient specification among the candidate of ARIMA models and has been automatically selected by auto-arima, which was based on the optimal fit criteria. The verdict validates the suitability of the seasonal ARIMA structure for modeling Mati's monthly tourist arrivals. This model employed in this study is the Seasonal Arima (1,1,3)(0,0,2)[12]. The specification discussed that the data required first-order differencing, which is the non-seasonal differencing (d=10) to achieve the stationarity, while there is no seasonal differencing was necessary (D=0). This also have inclusion of the seasonal moving average term (Q=2) this allows that pattern and shocks that occur annually, which is essential given the strong seasonal nature in tourism data.

In Table 2 based on the presented indices, the model yields a log-likelihood value of 1150, an AIC of 3113, an AICc of 3114, and BIC of 3134. This minimal difference between the AIC and AICc further approves that the model is parsimonious and well calibrated and identified no evidence of over-fitting. These statistics collectively demonstrate that the model provides a adequate balance between goodness-of-fit and complexity.

In Table 3, more findings revealed which is a highly seasonal yet gradually stabilizing the pattern. The model successfully captured the expected peaks and troughs throughout the year, and the point out the estimates converge to steady level over time, indicating long-term stability in tourist arrivals trends. The 95% confidence intervals also provide a reliable measure of the prediction uncertainty.

The diagnostic checks confirm that the Seasonal Arima (1,1,3)(0,0,2)[12] model is statistically complete, properly specified and suitable for the forecasting in monthly the arrivals of tourist in Mati City.

Table 2.*Model fit indices of the seasonal ARIMA model*

Fit Measure	Value
Log-Likelihood (LL)	−1550
AIC	3113
AICc	3114
BIC	3134

Note. LL = Log-likelihood; AIC = Akaike Information Criterion; AICc = corrected AIC; BIC = Bayesian Information Criterion.

Table 3 presents that the forecasted monthly arrivals of tourist in Mati City, produced using the Seasonal ARIMA (1,1,3) (0,0,2) [12] model. The forecasts extend from 2013 until 2023; this provides a point that estimates a 95% of confidence intervals for each month. These results reveal a highly seasonal, yet gradually stabilizing the pattern of the activity of the tourist. This initial forecast in the year of 2013 until 2015, predicts substantial variation in monthly influxes, ranging from approximately 31,000 arrivals in September, which revealed low season, to nearly 39,000 in December, overlapping during Christmas and New Year holidays. This pattern indicates that the tourism in Mati City is heavily direct influenced by seasonal tourism drivers, including the summer vacations, holiday celebrations, and favorable weather conditions during the dry months.

In 2016, the advanced estimate toward a steady-state of approximately 35,000 ot monthly arrivals, suggesting that the market of tourism in Mati City is approaching stabilization. The reduction of variability across years suggests a diminishing uncertainty, that means that the city in tourism sector is growing and less vulnerable in short-term shocks. Such as the stabilization consistent with the ARIMA model's identification of stationarity after first differencing, where the long-run fluctuations level off around the mean of equilibrium value. This statistical behavior implies, a periodic increases, while decreases continue due to seasonality, the total of annuals remain impartially constant.

The recurrent peaks in the months of April, May and December represent the city's dual tourism peaks, which are the summer and holiday travel periods. These months show the highest point of forecasts throughout the entire projection horizon, while August and September persistently emerge as off-season months with the lowest forecasts. This supports the notion tourism in Mati City, that demand cyclically structured, the feature is commonly in coastal and nature-based destinations dependent on the weather and schedules of the leisure. As in the predictability offers valuable insights for the tourism management, allowing the local authorities and hospitality providers to predict the arrival surges and the operational capacities of adjustment, staffing, and promotional activities accordingly.

From 2016 onward, the predictable values and their confidence intervals remain comparatively uniform across the months and years, with that the central forecasts holding at around 35,374 and the bounds widening slightly over time. This widening is

Table 3. *Forecasted monthly tourist arrivals in Mati City using Seasonal ARIMA(1,1,3)(0,0,2)[12] Model*

Month	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Jan	33,586 (14,580–52,591)	35,084 (11,260–58,907)	35,372 (6,904–63,839)	35,374 (2,999–67,750)	35,374 (−489–71,238)	35,374 (−3,667–74,416)	35,374 (−6,605–77,354)	35,374 (−9,350–80,099)	35,374 (−11,937–82,685)	35,374 (−14,389–85,137)	35,374 (−14,389–85,137)
Feb	32,360 (13,140–51,581)	34,781 (10,638–58,924)	35,376 (6,571–64,182)	35,374 (2,694–68,055)	35,374 (−765–71,513)	35,374 (−3,920–74,669)	35,374 (−6,841–77,589)	35,374 (−9,572–80,320)	35,374 (−12,146–82,894)	35,374 (−14,588–85,336)	35,374 (−14,588–85,336)
Mar	34,192 (14,651–53,733)	34,256 (9,772–58,741)	35,373 (6,219–64,527)	35,374 (2,392–68,357)	35,374 (−1,038–71,787)	35,374 (−4,172–74,921)	35,374 (−7,075–77,824)	35,374 (−9,792–80,540)	35,374 (−12,354–83,103)	35,374 (−14,786–85,534)	35,374 (−14,786–85,534)
Apr	34,935 (15,156–54,715)	36,232 (11,429–61,036)	35,375 (5,887–64,863)	35,374 (2,093–68,656)	35,374 (−1,310–72,058)	35,374 (−4,422–75,171)	35,374 (−7,308–78,057)	35,374 (−10,011–80,759)	35,374 (−12,561–83,310)	35,374 (−14,983–85,732)	35,374 (−14,983–85,732)
May	37,130 (17,062–57,198)	36,544 (11,413–61,675)	35,374 (5,548–65,199)	35,374 (1,796–68,953)	35,374 (−1,579–72,328)	35,374 (−4,670–75,419)	35,374 (−7,539–78,288)	35,374 (−10,229–80,977)	35,374 (−12,768–85,317)	35,374 (−15,180–85,928)	35,374 (−15,180–85,928)
Jun	36,156 (15,842–56,471)	35,913 (10,467–61,359)	35,375 (5,221–65,529)	35,374 (1,502–69,247)	35,374 (−1,846–72,595)	35,374 (−4,917–75,666)	35,374 (−7,770–78,519)	35,374 (−10,446–81,194)	35,374 (−12,973–83,722)	35,374 (−15,375–86,124)	35,374 (−15,375–86,124)
Jul	32,930 (17,110–48,751)	34,449 (12,960–55,939)	35,374 (4,892–65,857)	35,374 (1,210–69,538)	35,374 (−2,112–72,861)	35,374 (−5,163–75,911)	35,374 (−8,000–78,748)	35,374 (−10,662–81,410)	35,374 (−13,178–83,927)	35,374 (−15,375–86,124)	35,374 (−15,375–86,124)
Aug	33,242 (16,234–50,249)	34,310 (12,321–56,299)	35,375 (4,569–66,180)	35,374 (921–69,827)	35,374 (−2,375–73,124)	35,374 (−5,407–76,155)	35,374 (−8,227–78,976)	35,374 (−10,877–81,625)	35,374 (−13,382–84,131)	35,374 (−15,375–86,124)	35,374 (−15,375–86,124)
Sept	31,373 (13,518–49,229)	33,463 (11,008–55,919)	35,374 (4,248–66,500)	35,374 (635–70,114)	35,374 (−2,637–73,386)	35,374 (−5,649–76,398)	35,374 (−8,454–79,203)	35,374 (−11,091–81,839)	35,374 (−13,585–84,334)	35,374 (−15,375–86,124)	35,374 (−15,375–86,124)
Oct	32,566 (14,628–50,503)	34,195 (11,449–56,942)	35,374 (3,932–66,817)	35,374 (350–70,398)	35,374 (−2,897–73,646)	35,374 (−5,890–76,639)	35,374 (−8,680–79,429)	35,374 (−11,303–82,052)	35,374 (−13,787–84,536)	35,374 (−15,375–86,124)	35,374 (−15,375–86,124)
Nov	35,047 (16,591–53,503)	35,418 (12,272–58,564)	35,374 (3,617–67,131)	35,374 (68–70,681)	35,374 (−3,156–73,904)	35,374 (−6,130–76,878)	35,374 (−8,905–79,653)	35,374 (−11,515–82,264)	35,374 (−13,988–84,737)	35,374 (−15,375–86,124)	35,374 (−15,375–86,124)
Dec	38,820 (20,198–57,442)	36,769 (13,310–60,228)	35,374 (3,307–67,442)	35,374 (−212–70,960)	35,374 (−3,412–74,161)	35,374 (−6,368–77,117)	35,374 (−9,128–79,877)	35,374 (−11,727–82,475)	35,374 (−14,189–84,938)	35,374 (−15,375–86,124)	35,374 (−15,375–86,124)

Note. Values represent Point Forecasts with 95% Confidence Intervals (Lower–Upper Bounds). Forecasts are in estimated number of tourist arrivals per month.

a natural statistical property of ARIMA forecasts, as inconclusiveness accumulates with longer forecasting prospects. Yet, in the models of stability across forecasted years this suggested that the future tourist volumes are maintainable under the present infrastructure and promotional efforts. In the close-fitting clustering of confidence intervals up to 2023 indicates that the tourism sector revealed likely to maintain its current level of performance. Unless, the external shocks: such as global travel restrictions; infrastructure investments; or major marketing campaigns; change demand course. This incidence of negative lower bounds in early forecast intervals in the statistical nature of the ARIMA-based on the confidence estimation. To maintain the practical validity, these values were shortened to zero. Otherwise, the future studies may also consider a log-transformed SARIMA model to impose a non-negativity.

While the model indicates a stabilization of around 35,000 tourist arrivals monthly, this plateau should be interpreted carefully. In the ARIMA models, such as the behavior sometimes revealed, means a decline of essential in stationary processes rather than a true economic saturation. Thus, the observed equilibrium may represent a statistical artifact of the univariate model rather than confirmed capacity limit. The external restrictions such as infrastructure capacity; accessibility; and destination competitiveness must be inspected to validate whether this plateau reflects real-world boundaries.

Figure 4 highlights the distinct the seasonal dispersal in monthly arrival of tourists. The tourist of median counts are notably higher in the months of April, May and December, which were confirming the two main tourism peaks are the summer vacation period and the Christmas holidays. Otherwise, the lowest medians appear in the month of August as well in the month of September. These months are typically affected by opposing weather and fewer travel-related activities.

Table 4.*Monthly Tourist Arrivals in Mati City*

Month	Minimum	25th Percentile	Median	75th Percentile	Maximum
1	5,000	15,000	20,000	25,000	35,000
2	5,000	10,000	15,000	20,000	30,000
3	0	10,000	15,000	25,000	35,000
4	0	15,000	35,000	40,000	45,000
5	0	10,000	25,000	35,000	40,000
6	5,000	10,000	20,000	25,000	35,000
7	5,000	10,000	20,000	25,000	30,000
8	5,000	10,000	20,000	25,000	30,000
9	5,000	10,000	15,000	20,000	25,000
10	5,000	10,000	20,000	25,000	30,000
11	0	15,000	20,000	30,000	35,000
12	10,000	~20,000	30,000	50,000	55,000

The variability or the height of the boxes and whiskers, which also differ every month, this together with the wider range of high-tourism for the month of April and December, this shows a greater instability in arrivals during peak seasons, a common feature in data of tourism that influenced by unpredictable factors such as local festivals, transport capacity, or marketing campaigns. The pattern captured here strengthens the presence of strong seasonality, qualifying the incorporation of a seasonal ARIMA structure.

In Figure 2, the ARIMA model effectively captures the historical cyclical pattern of tourist arrivals, that indicating the noticeable seasonality and the irregular peaks. The section of forecast represented by the shaded region, projects an upward but stabilizing trend in the next cycle. The confidence bands widen increasingly, showing the increased forecast uncertainty over the longer prospects. The model’s central forecast line confirmed that the average monthly arrivals are expected to stabilize tourist around 35,000 to 38,000, with periodic upward deviations during the high seasons. The inclusion of the two seasonal the MA terms like the SMA1 and SMA2, allows the model to have smooth recurring spikes and dips, that ensuring the realistic seasonal forecasts. This visualization confirmed that the ARIMA (1,1,3) (0,0,2) [12] specification fits the tourism data, offering a reliable short-term projections for planning and policy purposes.

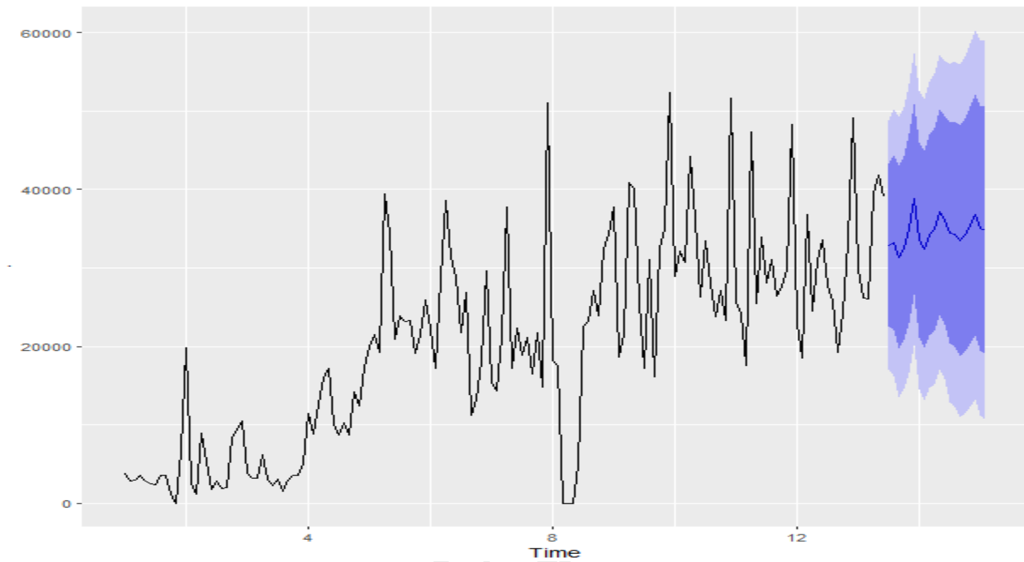

Figure 2. *Automatic ARIMA forecasts with 95% confidence intervals*

Table 5 reports the estimated analysis for the arrivals of tourist in Mati City, residual diagnostic of the seasonal ARIMA model validates the statistical adequacy of the ARIMA model. This absence of significant autocorrelation in residuals also implies that systematic information remains explainable, this shows that the model has the effectively captured the underlying process of a driving arrivals of tourist. The approximately zero, which means residuals further confirm forecast that there is no biased and the normal distribution of residuals indicates that model assumptions are satisfied.

These diagnostics confirmed that the ARIMA model provides reliable forecasts with significant specification or serial correlation, to enhancing confidence in the predicted values.

Table 5.*Residual diagnostics of the seasonal ARIMA model*

Diagnostic Test	**Expected Pattern**	**Interpretation**
Residual Mean	Approximately zero	Indicates an unbiased forecast.
Residual ACF	No significant Autocorrelation	Suggests white noise residuals.
Ljung–Box Q-test ($p > .05$)	Non-significant	Confirms independence of residuals
Histogram of Residuals	Near-normal distribution	Indicates residual normality and model adequacy.

The residual plot indicates that the residuals fluctuate randomly around zero, without a visible trend or the cyclical pattern remaining after the model fitting. The fullness of fluctuations appears constant, this suggesting that the homoscedastic residual variance is a main assumption of the ARIMA validity. Without the presence of serial correlation this implies that the model successfully captured all the systematic components of the time series, such as the trend, seasonality, and autocorrelation. Although some spikes look around the mid-series (roughly near t=8), these deviations are isolated and not persistent. In a minor residual outliers likely correspond to extraordinary events, such as tourism promotions or temporary disruptions. For example, the weather-related travel limitations. Collectively, this residual diagnostics checked that the model errors bear a resemblance to white noise, validating the model’s adequacy and predictive reliability by Box & Jenkins (1976).

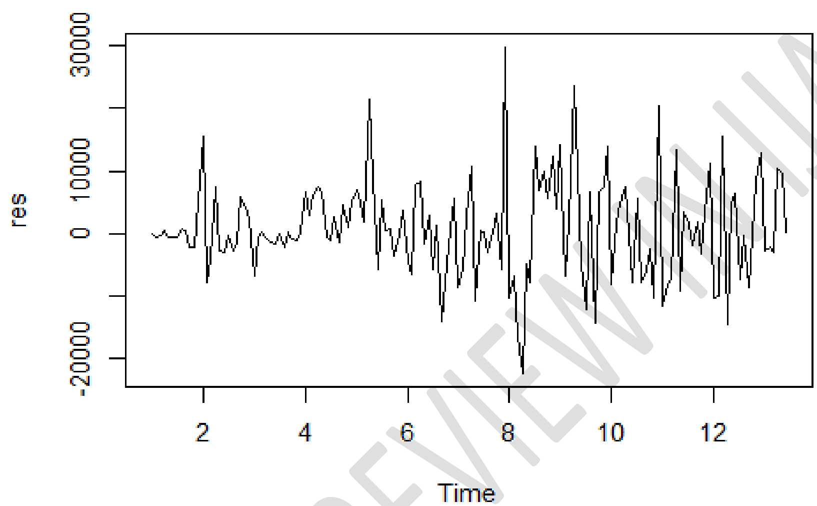

Figure 3. *Residual Plot of the ARIMA Model*

In the power of the time-series forecasting, this lies in the ability of the model to make a prediction. The Figure 5 shown, it that the blue forecast line indicates a stable long-term forecast level centered that near to 35,000 monthly arrivals tourist, while the expanding shaded region which represents the increasing uncertainty of forecast prospect extends. The firm widening of the prediction intervals shows the deepening of the uncertainty typical in ARIMA projections, where the stochastic shocks gather over time.

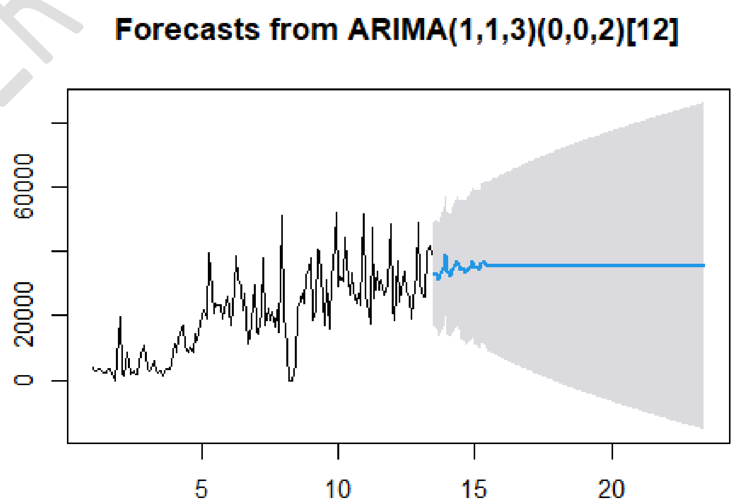

Figure 4. *Forecasts from ARIMA(1,1,3)(0,0,2)[12]*

Particularly, the model maintains mean stationarity in the dissimilarity series, which implies that the after adjusting for the trend and seasonality, the future values differ around the consistent equilibrium level. This plateau pattern proposes that, in the absence of most important exogenous intercessions such as: new infrastructure; destination marketing or external economic shifts; the tourism claim in Mati City is likely remain at current the average levels. Which means that the consistency between short-term forecasts indicated in the Figure 3 and the long-term predictions in Figure 5, reinforces the robustness and the reliability of the ARIMA model in capturing both cyclical and even the trend dynamics of tourism arrivals.

In the integration of these results with all the tables highlights that the Seasonal ARIMA model effectively that captured both the cyclical and stochastic variations in Mati City's monthly arrivals of tourists. The model's balanced AR and MA structure, low information criteria, and white-noise residuals collectively indicate that there a strong predictive validity. From the econometric standpoint, these findings affirmed that tourism demand follows a seasonally stationary process, which shown in the consistently Box–Jenkins theory, where the shocks disperse over time but often seasonally. The long-term forecast stabilization around 35,000 tourists per month suggests that without the major infrastructure or marketing shocks, the tourism industry maintains a steady-state equilibrium.

Finally, Table 6 shows that the possibility of a business implications based on the distinctions of the seasonal ARIMA forecasting of Mati City's tourist arrivals. This presents a structured synthesis of the core empirical findings from the seasonal ARIMA forecasting exercise, mapped in this study's objectives, and translated into business implications and stakeholder actions.

Table 6. *Alignment of main findings, business implications, and recommended actions based on seasonal ARIMA forecasting of tourist arrivals in Mati City*

Study Objective	Main Technical Findings (from SARIMA results)	Business / Managerial Implications	Recommended Actions / Responsible Stakeholders
1.Analyze seasonal patterns in tourist arrivals	Time-series decomposition and box-plots confirmed distinct cyclical peaks in April–May and December, and off-season lows in August–September. Seasonality is strong and statistically stable across years.	Tourism demand follows a predictable annual rhythm, allowing efficient scheduling of marketing, transport, and accommodation resources.	City Tourism Office – design a Seasonal Tourism Calendar (summer & holiday campaigns). Local hotels/resorts – implement peak-season pricing and reservation management. • DOT Region XI – integrate Mati's seasonal profile in regional promotions.
2. Identify the best-fit SARIMA model for forecasting monthly arrivals	The selected SARIMA (1,1,3)(0,0,2)[12] model showed low AIC = 3113 and BIC = 3134, with white-noise residuals and no serial correlation. Model adequately captures both short-term and seasonal dynamics.	The model provides statistically reliable short-term forecasts (~35 000 arrivals/month), serving as a quantitative basis for evidence-based tourism planning.	LGU Mati Planning and Development Office – embed forecast outputs in the Tourism Development Plan 2025–2030. Academe / UM-RPC – maintain a Forecasting Observatory updating monthly projections.
3. Generate short-term forecasts and assess future tourism trends	Forecasts indicate steady-state equilibrium around 35 000 arrivals/month from 2016 onward, with slowly widening confidence intervals (uncertainty increasing over time).	Mati's tourism market is maturing and stable, implying a need for product diversification rather than mere expansion.	City Tourism Council – develop new thematic experiences (eco-tourism, cultural circuits). Private investors / SMEs – target off-season niches (conventions, surfing events). DOT XI – support training for innovative tourism products.
4. Validate model adequacy through residual diagnostics	Residual mean ≈ 0; Ljung–Box p > .05; residuals normally distributed, confirming unbiased forecasts and model adequacy.	Confidence in forecasts enables data-driven budgeting and staffing, minimizing guesswork in resource allocation.	City Budget Office & Tourism Operations Office – link forecast data with annual operating plans. HR units of hospitality establishments – adjust seasonal workforce levels accordingly.
5. Translate forecasts into strategic and operational decisions	Forecast graphs (Figures 3 & 5) show stabilized demand plateau, meaning growth is contingent on exogenous shocks (infrastructure, marketing).	Without intervention, growth will remain constant; thus, strategic investments are needed to break the equilibrium.	LGU Mati & Provincial Government – invest in connectivity projects (roads, digital systems). DOT XI / TPB Philippines – launch destination branding campaigns emphasizing Mati's competitive assets.
6. Provide actionable recommendations for stakeholders	The combined results validate that the SARIMA model accurately captures trend, seasonality, and stochastic variations; shocks dissipate but reoccur annually.	Tourism growth must be managed through adaptive strategies responsive to recurrent seasonal shocks and external events.	Disaster Risk Reduction Office & Tourism Office – formulate weather-contingency tourism plans. Davao Chamber of Commerce and Industry – coordinate business continuity measures during monsoon months.

First, the consistency of seasonal peaks in April, May, and December, and troughs in August and September, as established in the decomposition and box-plot analysis, this aligns with the tourism demand patterns in many coastal or holiday-dependent destinations (Peiris, 2016; Bigovic, 2012).

Second, the identification of SARIMA (1,1,3) (0,0,2) [12] as the optimal model, with favorable fit metrics (AIC, BIC) and valid residual structure, demonstrates the methodological consistency. In the broader perspective of tourism-forecasting literature, the SARIMA is sometimes used as a benchmark model for the univariate forecasts through passing the white-noise residual tests and other diagnostic checks. In this model where the standard Box–Jenkins requirements meet, which can lend to credibility of the forecasted values.

Third, the forecasted stabilization of monthly arrival of tourist that around 35,000 from 2016 onward is a substantive perception. This implied that the reaching of a saturation or equilibrium were phase in visitors' volume, the absent of structural changes. In the business or any policy perspective this means that more growth may require an active intervention, such as new product development, improved connectivity, or the destination in similarities. In the forecasting caught an attention taken from the study of Hyndman &Athanasopoulos (2022) which mentioned that without the exogenous shocks or new interventions occur, the time-series forecasts tend to relapse in a long-run means that this behavior is consistent with the theoretical property of stationary ARIMA processes after differencing, wherein forecasts converge toward a long-run mean.

Fourth, in residual diagnostics the model adequacy under pin the reliability of these forecasts. The error terms show no remaining autocorrelation, suggesting that the approximately zero mean and approximate normal distribution, the forecasts can be treated as unbiased and efficient estimates. This level of diagnostic validation sometimes was not reported in empirical tourism most studies, but it is crucial to avoid overconfidence in forecasting (Moore & Tenney, 2023)

However, the forecasts rely on the assumption that past patterns persist, which may not hold in the presence of shocks such as pandemics, policy changes, and climate events, etc. In tourism forecasting in literature, as mentioned by Liang et al. (2022), some authors advocate hybrid or ensemble models combining the ARIMA with mechanism learning or explanatory variables to enhance the accuracy, especially when precariousness or structural change is present. Similarly, multivariate or spatially disaggregated models sometimes outdo simple univariate forecasts over longer the prospects (Arno et al., 2020).

4. Conclusion and Recommendation

The seasonal ARIMA (1,1,3) (0,0,2) [12] model successfully captured the complex dynamics of monthly arrivals in Mati City in tourism, integrating the short-term dependencies and pronounced seasonal cycles. These models' diagnostics confirmed that the residuals estimated with white noise and the parameter stability support a reliable inference. These forecasts generated a model that reveals a clear pattern of dual seasonal peaks that happen consistently in the months of April, May, and December, with troughs in August and September. This emphasizes the city's strongly cyclical tourism demand. Over time, the projected arrivals toward a steady-state equilibrium are roughly 35,000 visitors per month, indicating that the growth of the ceiling might be constrained, but some external changes also intervene. The widening of confidence intervals over the longer prospects shows the increase of uncertainty, yet the nearer-term forecasts remain sufficiently precise for planning purposes. The findings affirmed that while Mati's tourism exhibits predictability and stability under current conditions, meaningful growth beyond the forecast plateau likely depends on strategic interventions rather than expansion

Recommendation

Here are several findings in strategic and operational recommendations shown as follows:

First, the city government should lead the establishment of a Tourism Analytics Cell responsible for maintaining and updating forecasting models. This unit should be equipped with analytical tools, such as Python, R, or Excel-based forecasting systems, and data collection platforms, such as KoboToolbox, for real-time tourism monitoring. The capacity-building must be initiated, which includes training in time series analysis that analyzes the data visualization; this should be conducted in collaboration with academic institutions.

Second, the decision-makers and tourism operators should align in staffing, infrastructure maintenance, and marketing schedules with the expected seasonal peaks and troughs, which include preparing for surges in April, May, and December, and any anticipated slack demand in the months of August and September. The product diversification strategies should specifically target off-peak months (August–September). Instantly, eco-tourism programs, surfing events, cultural festivals, and conference tourism can be scheduled during these periods to ease the seasonal demand troughs and improve constant tourism distribution.

Third, to break the plateau in visitor volumes, Mati City should invest in the destination, such as eco-tourism trails, cultural festivals in the off-season, conference tourism, and niche attractions. These initiatives can alter the demand curve upward rather than redistributing the existing flows.

Fourth, the incremental infrastructure and connectivity upgrades, such as roads, transport, and digital amenities or facilities. That warrants priorities such as reducing friction costs as the most vigorous way to expand in the long run, increasing the capacity for the arrival of tourists.

Fifth, the city must adopt a scenario-based plan using the different forecasts under the hypothetical shock scenarios, such as natural disasters, global travel, and disruptions. This might help to prepare in advance for contingencies beyond the "business-as-usual" that the path suggested by ARIMA.

Finally, for future researchers and applications, the efforts should explore mixed or ensemble forecasting approaches that incorporate external predictors, such as economic gauges, weather data, promotional expenditures, or airline seat capacity. Possibly, this would enhance the accuracy and policy relevance.

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