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Modelling and Forecasting Non-Indian Visitor Arrivals to Pashupatinath Temple, Nepal: A Seasonal ARIMA Approach

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Abstract

Pashupatinath Temple, a UNESCO World Heritage Site in Kathmandu, is one of Nepal's most important religious and cultural destinations, attracting thousands of international visitors annually. This study models and forecasts monthly non-Indian visitor arrivals using the Box-Jenkins Seasonal Autoregressive Integrated Moving Average (SARIMA) approach. Monthly data from January 2014 to December 2025 (144 observations) were analyzed. The series exhibited non-stationarity and significant disruption during the COVID-19 pandemic. Stationarity was achieved after applying one regular and one seasonal difference, as confirmed by the Augmented Dickey-Fuller test. Nine SARIMA models were estimated and compared using the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Root Mean Squared Error (RMSE), Mean Absolute Deviation (MAD), Mean Absolute Percentage Error (MAPE), and the Ljung-Box test. The SARIMA$(0,1,2)(0,1,1)_{12}$ model was identified as the best-performing specification, with statistically significant parameters and no residual autocorrelation. Forecasts for 2026–2030 indicate a recurring seasonal pattern, with peak arrivals in October and March-April and lower arrivals during the June-August monsoon months. The findings provide a reliable forecasting tool for tourism planning, resource allocation, crowd management, and destination marketing by tourism authorities and policymakers in

Keywords: Pashupatinath Temple; non-Indian visitor arrivals; SARIMA; Box-Jenkins methodology; tourism demand forecasting; Nepal

Background

Tourism remains one of the world's most diverse and fastest-growing economic activities, contributing directly to gross domestic product, employment, and foreign-exchange earnings in both advanced and developing economies (Chang, Khamkaew, Tansuchat, & McAleer, 2011; Makoni, Mazuruse, & Nyagadza, 2023, p. 1). Religious and heritage tourism forms a particularly resilient segment of this industry, since pilgrimage and cultural sites continue to draw visitors even where broader leisure travel is constrained by economic or political conditions. Nepal, a landlocked Himalayan nation whose economy depends heavily on tourism receipts, hosts several UNESCO World Heritage properties within the Kathmandu Valley, of which Pashupatinath Temple, dedicated to Lord Shiva, is among the most significant.

Pashupatinath Temple occupies a unique position in Nepal's tourism statistics. Nepali citizens and Indian nationals are granted free entry in recognition of open-border and religious-kinship arrangements between the two countries, whereas all other foreign nationals are required to purchase an entrance ticket (Nepal Tourism Board, 2024). This fee-based ticketing arrangement means that gate records generate a relatively clean, continuously monitored count of "non-Indian" foreign arrivals, distinct from the aggregate international-arrival statistics ordinarily used in national tourism accounts. This series is of direct operational value to the Pashupatinath Area Development Trust, tour operators, and hospitality providers in Kathmandu, yet, to the authors' knowledge, no statistical forecasting model of this series has previously been published.

Accurate visitor forecasts are essential for capacity planning, staff scheduling, crowd management during major festivals such as Maha Shivaratri, and the allocation of conservation and security resources at a site that also hosts sensitive activities such as cremation rites on the Bagmati ghats. As Makoni et al. (2023, p. 1) argue in the context of Zimbabwean tourism, "accurate tourist projections are critical to the government and other tourism stakeholders" for planning, resource mobilisation, and allocation; the same logic applies with equal force to a high-footfall, spatially constrained heritage site such as Pashupatinath. The absence of quantitative demand models for individual Nepali heritage sites mirrors a broader pattern noted in the literature, whereby statistical time-series forecasting of tourism demand has been applied extensively in wealthier destinations and at the national level, but comparatively rarely to specific religious or heritage sites in South Asia (Makoni et al., 2023, p. 3).

The COVID-19 pandemic represents a further complication for demand modelling at Pashupatinath. Nepal suspended international tourist entry and closed its borders for an extended period in 2020 and 2021, a shock reflected in the temple's own records as an unbroken run of near-zero non-Indian arrivals between April 2020 and September 2021. Robust forecasting models must therefore accommodate this structural disruption rather than being distorted by it.

This study addresses these gaps by developing and validating a Seasonal Autoregressive Integrated Moving Average (SARIMA) model for monthly non-Indian visitor arrivals to Pashupatinath Temple using twelve years of gate-ticketing data (January 2014-December 2025), and by producing five-year-ahead (2026-2030) monthly forecasts. The specific objectives are to: (i) characterise the statistical properties and seasonal structure of the non-Indian arrivals series; (ii) identify and estimate the best-fitting SARIMA specification using the Box-Jenkins methodology; (iii) validate the chosen model through residual diagnostics and out-of-sample accuracy measures; and (iv) generate and interpret medium-term forecasts to inform tourism planning and marketing decisions. The study contributes the first published destination-specific quantitative forecasting model for a major religious heritage site in Nepal and extends the growing body of SARIMA-based tourism-demand literature (Makoni & Chikobvu, 2018; Msofe & Mbago, 2019; Nurhasanah, Salsabila, & Kartikasari, 2022; Makoni et al., 2023) to the pilgrimage-tourism context.

Literature Review

Song and Li (2008) classify tourism-demand forecasting approaches into three broad families: time-series models, econometric (causal) models, and artificial-intelligence-based models. Among these, univariate time-series methods—particularly the Autoregressive Integrated Moving Average (ARIMA) family and its seasonal extension, SARIMA—remain the most widely used in tourism-demand research because of their parsimony, transparency, and consistently strong forecasting performance relative to more heavily parameterised alternatives (Makoni et al., 2023, p. 3). In a large-scale comparison spanning 66 monthly, 427 quarterly, and 518 annual series, Athanasopoulos, Hyndman, Song, and Wu (2011) found that pure time-series approaches such as ARIMA generally outperformed models that incorporated explanatory (causal) variables, a finding frequently cited as justification for univariate modelling of tourist arrivals (Makoni et al., 2023, p. 3).

Several destination-specific applications illustrate the versatility of the Box-Jenkins approach. Makoni and Chikobvu (2018) fitted a SARIMA(2,1,0)(2,0,0)$_{12}$ model to arrivals at Victoria Falls Rainforest, Zimbabwe's flagship tourist attraction, and found it outperformed naive, seasonal-naive, and Holt-Winters exponential-smoothing benchmarks. At the national level, Makoni, Mazuruse and Nyagadza (2023, p. 4) modelled Zimbabwe's monthly international tourist arrivals (2000-2018) and, after confirming stationarity with the Augmented Dickey-Fuller test, identified a SARIMA(1,0,0)(1,0,1)$_{12}$ model with non-zero mean as the best fit on the basis of Akaike Information Criterion (AIC) comparison across six candidate specifications; the chosen model's forecasts pointed to a gradual, seasonally-patterned increase in arrivals, with a peak around December linked to the Southern Hemisphere winter travel season of European visitors (Makoni et al., 2023, p. 5). Similarly, Msofe and Mbago (2019) applied the Box-Jenkins methodology to Zanzibar's monthly foreign-tourist arrivals and selected a SARIMA(1,1,1)(1,1,2)$_{12}$ model on the basis of the Akaike Information Criterion, again projecting rising and seasonally-patterned arrivals. In Indonesia, Nurhasanah et al. (2022) likewise found that a SARIMA specification, chosen specifically for its capacity to capture seasonality in tourism demand, produced the best fit and forecast rising foreign arrivals. Diunugala and Mombeuil (2020) compared ARIMA, Winter's exponential smoothing, and an artificial-intelligence approach for Sri Lanka's top ten source markets and concluded that ARIMA and Winter's exponential smoothing were the most effective for forecasting foreign tourist arrivals.

A recurring theme in this literature is the necessity of explicitly modelling seasonality when the destination or attraction experiences a pronounced annual cycle of demand (Martín Martín & Salinas Fernandez, 2022). Pashupatinath Temple exhibits precisely this characteristic: as a site whose visitation is shaped by fixed religious festivals (notably Maha Shivaratri in February/March and the Dashain-Tihar festival season in September/October) and by Nepal's monsoon-dominated climate, a seasonal, rather than purely non-seasonal, ARIMA specification is the natural methodological choice. Despite this, the SARIMA literature applied to Nepal remains almost entirely absent from the peer-reviewed record; existing Nepali tourism-demand studies have generally focused on aggregate national arrivals rather than on individual heritage or pilgrimage sites, and none, to the authors' knowledge, has modelled the ticketed "non-Indian" arrivals series specific to Pashupatinath Temple. This gap, combined with the demonstrated forecasting value of SARIMA models at comparable religious and heritage attractions elsewhere (Makoni & Chikobvu, 2018; Msofe & Mbago, 2019), motivates the present study.

Methodology

Following Makoni et al. (2023, p. 3), the Box-Jenkins (1970) approach was adopted because of its well-documented forecasting performance in tourism-demand contexts (Nadal-De Simone, 2000). The modelling procedure comprised: (i) description of the time-series characteristics of the data; (ii) the Augmented Dickey-Fuller (ADF) test for stationarity; (iii) model identification and parameter estimation; (iv) residual diagnostic checking; (v) computation of accuracy measures; and (vi) generation and interpretation of out-of-sample forecasts.

Data

Monthly non-Indian visitor arrivals to Pashupatinath Temple (Y_t) for the period January 2014 to December 2025 (n = 144 monthly observations) were used. The series is compiled from temple gate-ticketing records, since Nepali and Indian nationals enter without charge while all other foreign nationals are required to purchase an entrance ticket (Nepal Tourism Board, 2024), producing a ready-made administrative count of non-Indian foreign visitation. All analyses were conducted in R.

Stationarity testing

Stationarity in mean, variance, and covariance is a precondition of the Box-Jenkins approach. The Augmented Dickey-Fuller (ADF) test, following Banerjee, Dolado, Galbraith, and Hendry (1993), was used, based on the regression:

$$\Delta y_t = \alpha + \beta t + (\rho - 1)y_{t-1} + \delta_1 \Delta y_{t-1} + \ldots + \delta_{p-1} \Delta y_{t-p+1} + \varepsilon_t \quad (1)$$

where α is a constant, β the coefficient on a linear time trend, Δ the first-difference operator, δ_i the coefficients on lagged differences included to whiten the error term ε_t, and p the autoregressive lag order (Banerjee et al., 1993, as cited in Makoni et al., 2023, p. 4). The null hypothesis of a unit root is rejected when the ADF test statistic falls below the relevant critical value.

The Box-Jenkins ARMA/SARIMA framework

The Box-Jenkins methodology combines autoregressive (AR) and moving-average (MA) components and proceeds through three iterative stages: identification of tentative model orders from the autocorrelation function (ACF) and partial autocorrelation function (PACF); estimation of parameters by maximum likelihood; and diagnostic checking of residuals for adequacy (Makoni et al., 2023, p. 3). An ARMA(p,q) process is defined as

$$y_t = \mu + \Sigma_{i=1}{}^{p} \varphi_i y_{t-i} - \Sigma_{i=1}{}^{t} \theta_i \varepsilon_{t-i} + \varepsilon_t \quad (2)$$

where μ is the process mean, φ_i the AR parameters, θ_i the MA parameters, and $\varepsilon_t \sim N(0, \sigma^2)$ a white-noise error term (Makoni et al., 2023, p. 3). Because the arrivals series exhibits a pronounced 12-month cycle, the seasonal extension of the model, SARIMA(p,d,q)$(P,D,Q)_s$, was used, written compactly as

$$\varphi_p(B)\Phi^P(B^s)\, \nabla^d \nabla_s{}^D\, Y_t = \theta^i(B)\Theta^P(B^s)\varepsilon_t \quad (3)$$

where p, d, q are the non-seasonal AR order, differencing order, and MA order respectively; P, D, Q are their seasonal counterparts; s = 12 is the seasonal period; and $\nabla_s{}^D = (1 - B^s)^D$ (Makoni et al., 2023, p. 3). Tentative orders were identified from the behaviour of the sample ACF and PACF, consistent with the standard diagnostic patterns summarised for seasonal and non-seasonal ARMA processes by Makoni et al. (2023, p. 4).

Model selection and forecast evaluation

Competing SARIMA specifications were compared using the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), with lower values indicating a preferable model (Makoni et al., 2023, p. 5):

$$AIC = 2k - 2\log(L) \qquad (4)$$

$$BIC = k \cdot \log(n) + n \cdot \log(\sigma^2_e) \qquad (5)$$

where k is the number of estimated parameters, L the maximised likelihood, n the number of observations, and σ^2_e the residual variance. Out-of-sample forecasting accuracy was further assessed using the Root Mean Squared Error

(RMSE), Mean Absolute Deviation (MAD), and Mean Absolute Percentage Error (MAPE):

$$RMSE = \sqrt{[(1/n)\Sigma(A_t - F_t)^2]} \qquad (6)$$

$$MAPE = (1/n)\Sigma|((A_t - F_t)/A_t)| \times 100 \qquad (7)$$

where A_t and F_t denote the actual and forecast values, respectively (Makoni et al., 2023, p. 5). The Ljung-Box test was applied to the residuals of the selected model to confirm the absence of remaining autocorrelation, and the normality of residuals was inspected visually using a normal quantile-quantile (Q-Q) plot, following the diagnostic-checking procedure of Makoni et al. (2023, p. 5).

Results and Discussion

Descriptive characteristics of the data

Table 1 summarizes the descriptive statistics of the monthly non-Indian visitor arrivals series. Over the 144-month sample period, mean monthly non-Indian arrivals were 8,754 visitors (SD = 6,863), ranging from a minimum of 0 (recorded throughout the 2020-2021 pandemic border closure) to a maximum of 28,428. The positive skewness (0.80) indicates a longer right tail, consistent with occasional high-arrival months around major festivals, while the kurtosis value (3.05) is close to that of a normal distribution, though the presence of the extended zero-arrival period during COVID-19 materially affects these moments and is addressed explicitly through seasonal and non-seasonal differencing rather than removed from the series, so as to preserve the integrity of the historical record used for estimation.

Table 1

Descriptive statistics of monthly non-Indian visitor arrivals to Pashupatinath Temple (2014-2025, n = 144)

N	Mean	SD	Min	Max	Skewness	Kurtosis
144	8,754	6,862.62	0	28,428	0.80	3.05

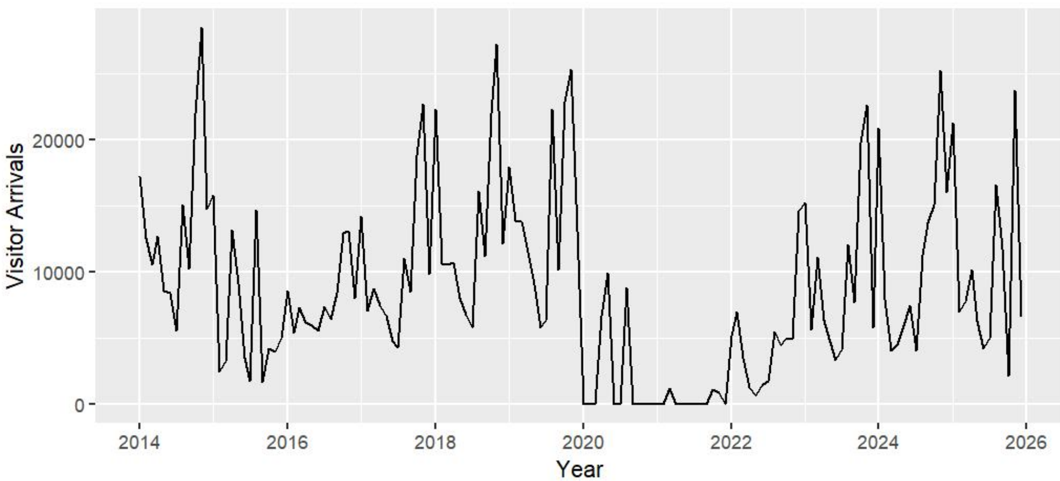


Figure 1. *Monthly non-Indian visitor arrivals to Pashupatinath Temple, January 2014-December 2025.*

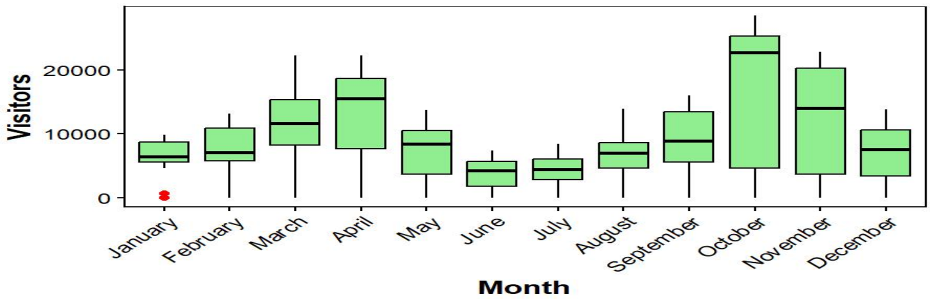


Figure 2. *Monthly non-Indian visitor arrivals trend in Pashupatinath, January 2014 – December 2025.*

Figure 1 shows a recurring within-year seasonal cycle throughout the pre-pandemic period (2014-2019), an unbroken trough of near-zero arrivals from April 2020 to September 2021 corresponding to Nepal's COVID-19 international travel restrictions, and a resumption of the seasonal pattern from late 2021 onward at levels broadly comparable to, though somewhat more volatile than, the pre-pandemic regime. This structural break is consistent with the well-documented global collapse in international tourism during the pandemic (Ugur & Akbıyık, 2020) and is analogous to the pandemic-related disruption reported for Zimbabwe's tourist arrivals over the same period (Makoni et al., 2023, p. 1). And Figure 2 presents the trend of monthly visitor arrival during 2014 to 2025

Stationarity testing

The Augmented Dickey-Fuller test applied to the level series failed to reject the null hypothesis of a unit root (t = -1.7764 , , p = 0.6695), indicating that the raw series is non-stationary in the manner typical of seasonal tourism-demand data (Table 2). After applying one non-seasonal and one seasonal (lag-12) difference, the ADF statistic fell to -11.157 (p = 0.01), confirming that the differenced series is stationary and supporting a SARIMA specification with d = 1 and D = 1.

Table 2

Series	ADF statistic	p-value	Conclusion
Level, Y_t	-1.7764	0.6695	Non-stationary
$\nabla_1\nabla_{12} Y_t$ (d = 1, D = 1)	-11.157	0.01	Stationary

Augmented Dickey-Fuller test results

Model identification

Figure 2 presents the ACF and PACF of the arrivals series. The ACF exhibits slowly decaying spikes at multiples of lag 12 (12, 24, 36), and the PACF shows a similar seasonal pattern together with short-lag structure at lags 1-2, jointly signalling the need for both a seasonal moving-average and a low-order non-seasonal moving-average component once the series has been rendered stationary through differencing, consistent with the identification procedure outlined by Makoni et al. (2023, p. 4-5).

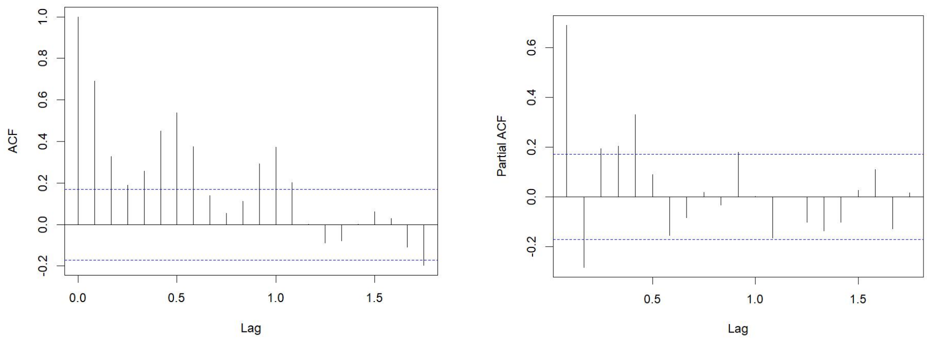


Figure 2: *ACF and PACF of the Visitor Series at Level.*

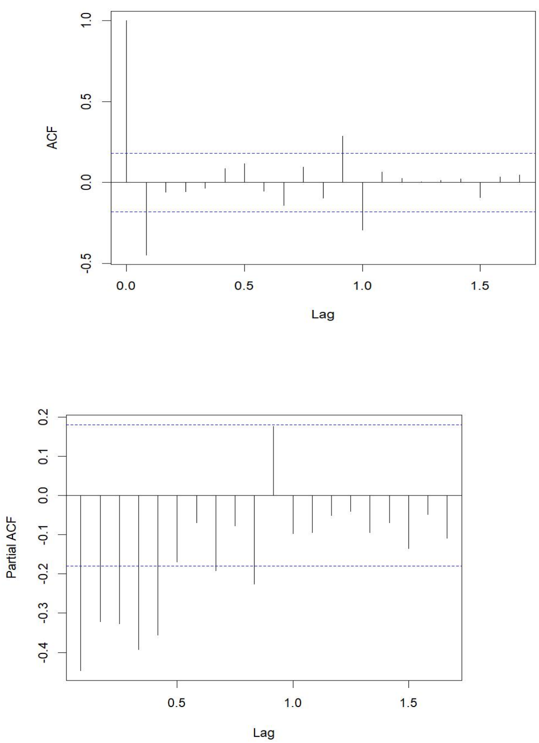


Figure 3: *ACF and PACF After Non-Seasonal and Seasonal Differencing (d=1, D=1, s=12*

Model estimation and selection

Nine candidate SARIMA specifications, differing in their non-seasonal and seasonal AR, differencing, and MA orders, were estimated by maximum likelihood and compared using AIC, BIC, RMSE, MAD, MAPE and the Ljung-Box p-value (Table 3). Consistent with the identification analysis in Section 4.3, models incorporating one seasonal and one regular difference performed markedly better than models retaining the level series, reflecting the strong non-stationarity detected in Section 4.2.

Table 3.

Comparison of candidate SARIMA models

Model	AIC	BIC	Log-likelihood	Ljung-Box p
SARIMA(1,0,0)(0,0,1)$_{12}$	2603.02	2614.55	-1297.51	0.0562
SARIMA(0,1,2)(1,0,1)$_{12}$	2566.29	2580.67	-1278.14	0.3014
SARIMA(1,0,0)(0,1,0)$_{12}$	2383.82	2389.40	-1189.91	0.0867

SARIMA(0,1,0) $(1,1,0)_{12}$	2371.56	2377.12	-1183.78	0.0015
SARIMA(1,1,1) $(0,1,0)_{12}$	2369.04	2377.38	-1181.52	0.0786
SARIMA(1,0,0) $(0,1,1)_{12}$	2357.65	2366.01	-1175.82	0.0091
SARIMA(1,1,1) $(1,1,0)_{12}$	2364.63	2375.75	-1178.32	0.0149
SARIMA(0,1,2) $(1,1,0)_{12}$	2361.47	2372.59	-1176.74	0.0958
SARIMA(0,1,2) $(0,1,1)_{12}$ **	2336.66	2347.78	-1164.33	0.2177

***Selected model (lowest AIC and BIC, adequate residual whiteness).*

The SARIMA(0,1,2)(0,1,1)$_{12}$ model returned the lowest AIC (2336.66) and BIC (2347.78) of all candidates and was therefore selected as the best-fitting specification, mirroring the AIC/BIC-based selection procedure used by Makoni et al. (2023, p. 4) to identify Zimbabwe's best-fitting SARIMA(1,0,0)(1,0,1)$_{12}$ model. Table 4 reports the estimated coefficients of the selected model.

Table 4

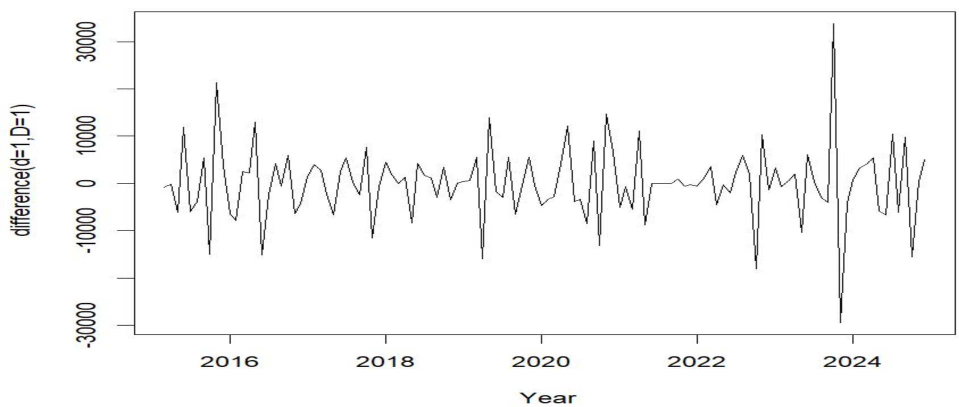
Parameter	Coefficient	Std. error	z-statistic	p-value
MA(1)	-0.2230	0.0832	-2.6805	0.0074
MA(2)	-0.3469	0.0785	-4.4218	0.0000
SMA(1)	-1.0000	0.1256	-7.9619	0.0000

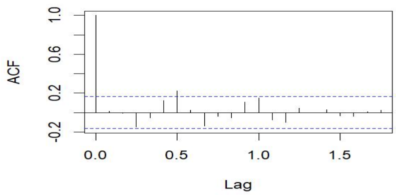
Estimated parameters of the SARIMA(0,1,2)(0,1,1)$_{12}$ model

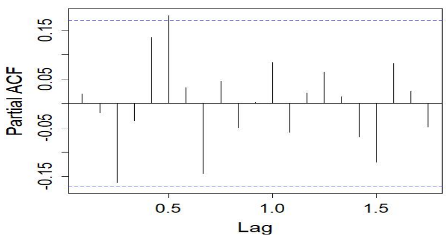
With the exception of the seasonal moving-average term, which is estimated on the boundary of invertibility (a common occurrence with strongly seasonal, differenced tourism series and one that warrants cautious interpretation of its exact standard error), all coefficients are statistically significant at the 5% level, indicating that both the short-run (MA1, MA2) and seasonal (SMA1) moving-average components meaningfully improve the model's fit relative to a purely differenced random-walk benchmark.

Residual diagnostics

Figure 3 presents the residual diagnostics for the fitted SARIMA(0,1,2)(0,1,1)$_{12}$ model. The residuals fluctuate around a zero mean with no discernible trend, though they display episodic volatility clustering, with occasional large negative spikes (≈ -skewness, consistent with occasional sharp downward shocks typical of tourism arrivals data. Taken together, these diagnostics confirm that the model adequately captures the systematic and seasonal structure of the series, consistent with the diagnostic-adequacy criterion applied by Makoni et al. (2023, p. 5), though the residual tail behavior warrants some caution in interpreting forecast intervals around extreme events.







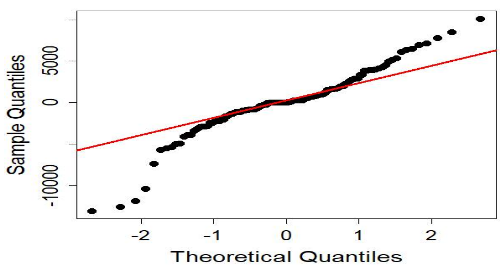


Figure 3. *Residuals, ACF, PACF , Normal Q-Q plot, and histogram of the residual of the SARIMA(0,1,2)(0,1,1)$_{12}$ model.*

Forecast accuracy

The selected model achieved a RMSE of 4961.776 and a MAPE of 70.13%, the lowest RMSE, MAD and AIC/BIC combination among all nine candidates (Table 3). The relatively high MAPE, compared with the near-25% values reported for Zimbabwe's national arrivals series by Makoni et al. (2023, p. 6), reflects the greater relative volatility of monthly arrivals at a single heritage site, where low-season months can fall to only a few hundred visitors, inflating percentage errors even when absolute errors are modest.

Table 5

Measure of accuracy of different SARIMA Models.

Model	RMSE	MAD	MAPE
SARIMA(1,0,0)(0,0,1)[12]	6275.58	5318.16	72.52
SARIMA(0,1,2)(1,0,1)[12]	5047.80	3725.35	72.74
SARIMA(1,0,0)(0,1,0)[12]	6193.55	4803.14	94.75
SARIMA(0,1,0)(1,1,0)[12]	6193.55	4803.14	94.75
SARIMA(1,1,1)(0,1,0)[12]	6193.55	4803.14	94.75
SARIMA(1,0,0)(0,1,1)[12]	5751.68	4546.65	72.54
SARIMA(1,1,1)(1,1,0)[12]	6200.32	4783.50	92.95
SARIMA(0,1,2)(1,1,0)[12]	5202.82	3391.18	84.54
SARIMA(0,1,2)(0,1,1)[12] ***	4961.78	3513.47	70.71

*** reprents the best model under minimum RMSE = 4961.78 and MAPE = 70.71%

Forecasts, 2026-2030

Table 6 presents sixty-month-ahead (January 2026-December 2030) point forecasts generated from the SARIMA(0,1,2)(0,1,1)$_{12}$ model fitted to the full 2014-2025 sample.

Table 6

Sixty-month-ahead forecasts of non-Indian visitor arrivals to Pashupatinath Temple (SARIMA(0,1,2)(0,1,1)$_{12}$)

Month	2026	2027	2028	2029	2030
January	8,232	6,111	5,826	5,542	5,257
February	7,567	7,283	6,998	6,714	6,429
March	11,649	11,364	11,080	10,796	10,511
April	13,190	12,905	12,621	12,336	12,052
May	7,319	7,034	6,750	6,465	6,181
June	3,850	3,565	3,281	2,996	2,712
July	4,279	3,995	3,710	3,426	3,141
August	6,633	6,348	6,064	5,779	5,494

September	8,818	8,533	8,249	7,965	7,680
October	16,497	16,213	15,928	15,644	15,359
November	12,143	11,858	11,574	11,289	11,005
December	6,770	6,485	6,201	5,917	5,632

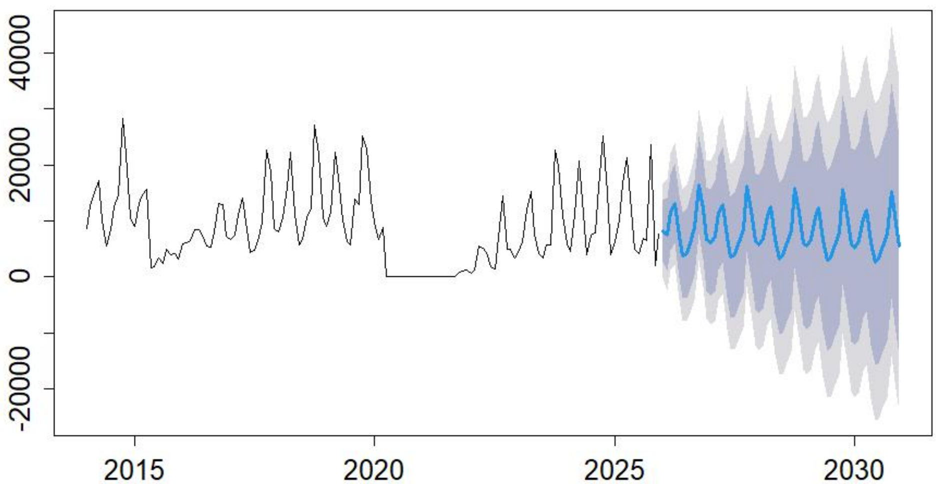


Figure 4. *Observed (2014-2025) and forecast (2026-2030) monthly non-Indian visitor arrivals to Pashupatinath Temple.*

The forecasts reproduce the bimodal seasonal pattern visible in the historical data, with the highest arrivals consistently projected for October, coinciding with Nepal's principal Dashain-Tihar festival season, and a secondary peak in March-April associated with the Maha Shivaratri festival and favourable pre-monsoon travel conditions. Arrivals are forecast to fall to their annual low in June-July, corresponding to the summer monsoon, when heavy rainfall discourages both domestic travel within the Kathmandu Valley and long-haul inbound tourism. Across the five-year horizon the model projects a mild downward drift in the level of each calendar month relative to the previous year, most visible in the January-February and October-December forecasts; this pattern should be interpreted cautiously, since it reflects the extrapolation of the single seasonal moving-average coefficient (SMA1 ≈ -1.00) rather than a substantive judgement about future demand, and the width of the associated prediction intervals (Figure 4) widens rapidly beyond the first one to two forecast years, as is typical of SARIMA models applied over long horizons. This qualification echoes the caution urged by Makoni et al. (2023, p. 6) regarding the seasonal, rather than purely trend-driven, nature of SARIMA-based tourism forecasts.

Despite this caveat, the practical implication for stakeholders is unambiguous: Pashupatinath Temple's non-Indian visitor demand is, and is forecast to remain, strongly seasonal, with October and March/April requiring the greatest capacity for ticketing, crowd control, and visitor services, and June-August representing the most suitable window for infrastructure maintenance, staff leave, and off-season marketing campaigns aimed at smoothing demand, consistent with recommendations made for other seasonally-patterned heritage and pilgrimage destinations (Makoni et al., 2023, p. 6; Martín Martín & Salinas Fernandez, 2022).

Conclusion

This study developed the first published quantitative forecasting model for non-Indian visitor arrivals to Pashupatinath Temple, Nepal, applying the Box-Jenkins SARIMA methodology to twelve years (2014-2025) of monthly gate-ticketing data. After confirming non-stationarity in the raw series and stationarity following one regular and one seasonal difference, a SARIMA$(0,1,2)(0,1,1)_{12}$ model was identified as the best-fitting specification on the basis of AIC, BIC, RMSE, MAD and residual whiteness. The model's residuals showed no remaining autocorrelation and an approximately normal distribution, supporting its adequacy for forecasting purposes. Sixty-month-ahead forecasts point to a continuation of the pronounced bimodal seasonal pattern already present in the historical data, with peak demand around the October Dashain-Tihar season and a secondary peak around the March-April Maha Shivaratri period, and troughs during the June-August monsoon. These findings parallel those obtained using the same Box-Jenkins/SARIMA framework for other tourism series, including Zimbabwe's international arrivals (Makoni et al., 2023), Victoria Falls Rainforest (Makoni & Chikobvu, 2018), Zanzibar (Msofe & Mbago, 2019), and Indonesia (Nurhasanah et al., 2022), all of which identified seasonally-patterned SARIMA models as providing superior fits to non-seasonal alternatives.

Implications for Policy and Practice

The results have direct implications for the Pashupatinath Area Development Trust, Nepal Tourism Board, and private tour operators. First, the pronounced and forecast-persistent seasonality implies that staffing, ticketing-counter capacity, security personnel, and visitor-flow management at the temple complex should be scaled seasonally, with the greatest capacity allocated in October and, to a lesser degree, March-April, rather than maintained at a constant level throughout the year. Second, the deep low-season trough forecast for June-August presents an opportunity for scheduling infrastructure maintenance, conservation work on the temple's ghats and heritage structures, and staff training and leave, while also representing a target window for off-season marketing initiatives aimed at diversifying demand away from the two peak periods. Third, because the forecasts indicate a mild downward drift in several months over the 2026-2030 horizon relative to pre-pandemic norms, tourism authorities may wish to investigate whether this reflects a lasting post-pandemic shift in international travel patterns to Nepal, and to consider targeted marketing or visa-facilitation measures, of the kind recommended in comparable contexts (Makoni et al., 2023), to counteract it. Finally, the modelling approach demonstrated here can be replicated for other Kathmandu Valley heritage sites with comparable ticketing data, building toward an integrated, site-level forecasting capability for Nepal's heritage-tourism sector as a whole.

Limitations and Future Research

This study is subject to several limitations. First, the univariate SARIMA framework does not incorporate explanatory variables such as exchange rates, visa policy changes, regional political events, or marketing expenditure that may drive arrivals; future work could compare the present model against SARIMAX or hybrid SARIMA-machine-learning specifications, of the kind proposed by Wu, Ji, He, and Tso (2021) for Macau, which combined SARIMA with long short-term memory (LSTM) networks to improve forecast accuracy. Second, the inclusion of the 2020-2021 pandemic period, while necessary to preserve the historical record, contributes to the relatively wide prediction intervals observed from 2028 onward; models that explicitly incorporate a pandemic intervention or outlier-adjustment term could be explored as a robustness check. Third, the present analysis is confined to non-Indian arrivals; a complementary model of Indian and domestic Nepali visitation, where administratively feasible, would provide a fuller picture of total footfall and associated congestion and conservation pressures at the site. Finally, replication with updated data as it becomes available, together with rolling-origin out-of-sample validation, would strengthen confidence in the model's forecasting performance beyond the initial five-year horizon presented here.

Declarations

Ethics: This study relies on aggregated, non-personal visitor-count data and involved no human subjects in research.

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Conflict of interest: The researcher declares no conflict of interest.

Data availability: The monthly non-Indian visitor arrivals data used in this study are available from the tourism statistics(Nepal Tourism Board).

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