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Article

Forecasting Post-Pandemic Tourist Arrivals in Himachal Pradesh: A SARIMAX Intervention-Analysis

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Abstract: This study forecasts total, domestic, and international tourist arrivals in Himachal Pradesh, a Himalayan state in northern India dependent on tourism. Using 132 months of data (January 2015–December 2025), the analysis addresses two major disruptions in the series: the COVID-19 collapse (February 2020–December 2021) and the July–August 2023 flood event. An intervention-adjusted Seasonal Autoregressive Integrated Moving Average with eXogenous regressors (SARIMAX) model is developed and compared with a Holt-Winters exponential smoothing (ETS) model and a standard seasonal ARIMA model without intervention variables. Stationarity tests confirm that the total-arrivals series requires first-order differencing. A SARIMAX model with COVID and flood dummy variables is selected using the Akaike Information Criterion and validated against 2025 as a held-out test year. The intervention-adjusted model outperforms the alternatives across all evaluation metrics (RMSE, MAE, MAPE, and Theil's U), and its residuals show no significant autocorrelation ($p > 0.05$). The flood variable is a statistically significant negative predictor ($p < 0.01$), while the COVID variable, despite its large economic impact, and is not statistically significant, as differencing already accounts for much of the shock. The validated model is re-estimated on the full dataset and forecast forward 36 months, projecting a gradual, seasonally uneven recovery, with annual arrivals reaching approximately 16.1, 17.1, and 18.1 million in 2026, 2027, and 2028—still below the 2017 pre-pandemic peak of 19.6 million. This study offers destination management organizations a practical, evidence-based forecasting tool and highlights the value of intervention time-series methods for mountain tourism economies facing recurrent shocks.
Keywords: tourism demand forecasting, SARIMAX, intervention analysis, time series, Himachal Pradesh, COVID-19, natural disaster, exponential smoothing

1. Introduction

Tourism is one of the most seasonally volatile and shock-sensitive branches of the services economy, and few destinations illustrate this more clearly than the Indian Himalayan state of Himachal Pradesh. Framed by snow-capped ranges, hill stations such as Shimla, Manali, and Dharamshala, and a well-developed base of religious, adventure, and leisure tourism, the state's travel and tourism sector has historically contributed a substantial share of the state's gross domestic product and rural non-farm employment (Anshul et al. n.d.; Kumar et al. 2026). Because so much of the state's economic activity hospitality, transport, handicrafts, and agri-tourism is directly or indirectly tied to visitor footfall, accurate short- and medium-term forecasts of tourist arrivals are not a mere statistical exercise but an input into hotel capacity planning, government revenue projection, transport scheduling, and disaster-preparedness budgeting.

The decade between 2015 and 2025 subjected Himachal Pradesh's tourism economy to two shocks of very different character. The first, the COVID-19 pandemic, produced an almost total collapse of arrivals for nearly two years: monthly domestic arrivals fell from a pre-pandemic range of roughly 1.0–2.1 million to as low as 23 recorded arrivals in April 2020, before a slow, uneven recovery through 2021. The second, the July–August 2023 monsoon floods and landslides that damaged roads, bridges, and hotel infrastructure across the state, produced a sharper but shorter-lived disruption superimposed on an otherwise recovering series. Conventional univariate forecasting methods, which implicitly assume that the statistical properties of a series are stable, or at most trend- and seasonality-driven, are not well suited to series containing such large, dateable, non-repeating interruptions. If the interruptions are not explicitly modelled, they can badly distort parameter estimates, inflate forecast uncertainty, and bias point forecasts for years after the event has passed.

This study addresses that problem directly. Using the complete monthly time series of domestic and international tourist arrivals to Himachal Pradesh from January 2015 to December 2025 (132 observations), it constructs and compares three forecasting approaches:

1. Seasonal ARIMA model with eXogenous intervention dummies (SARIMAX) that explicitly represents the COVID-19 and flood periods as structural breaks.
2. Holt-Winters exponential smoothing (ETS) state-space model that captures trend and seasonality but no explicit interventions
3. Seasonal ARIMA model of identical order to the SARIMAX specification but without the intervention regressors, included as a diagnostic benchmark to isolate the marginal contribution of the dummy variables.

All three models are evaluated out-of-sample on a genuine 12-month hold-out (calendar year 2025) that the models never see during estimation, and the best-performing specification is then refit on the full sample and used to generate point and interval forecasts for the 36 months from January 2026 to December 2028.

The remainder of the paper is organized as follows. Section 2 reviews the literature on tourism demand forecasting, with particular attention to SARIMA/SARIMAX and exponential-smoothing approaches, intervention and interrupted-time-series methods for modelling shocks, and prior forecasting work specific to Himachal Pradesh and comparable mountain and disaster-exposed destinations. Section 3 details the data and the econometric methodology, including stationarity testing, model identification, and the accuracy metrics used for out-of-sample comparison. Section 4 reports the findings: descriptive statistics, stationarity test results, the fitted SARIMAX specification, comparative forecast-accuracy statistics, and the 2026–2028 forecast itself, with supporting tables and charts. Section 5 discusses the results in the context of the wider tourism-forecasting literature and the practical realities of Himachal Pradesh's tourism economy, and Section 6 concludes with limitations and directions for future research.

2. Literature Review

2.1 Tourism demand forecasting: an overview

Tourism demand forecasting has matured into one of the most active sub-fields of applied forecasting research, spurred by the perishability of tourism services and the high cost of both under- and over-provisioning capacity (Shujie Shen, Gang Li, and Haiyan Song 2008). Song and Li's influential review traced the field's evolution from simple time-series extrapolation toward causal econometric models and, later, artificial-intelligence methods, a trajectory subsequently updated by (Song, Qiu, and Park 2019), who catalogued the growing role of big data and machine learning without displacing classical time-series benchmarks. (Peng, Song, and Crouch 2014) meta-analysis of sixtyfive forecasting studies published between 1980 and 2011 found that dynamic econometric and advanced time-series models including ARIMA and structural time-series specifications systematically outperform naive and basic exponential-smoothing benchmarks, a finding that motivates the present study's use of an intervention-adjusted ARIMA-family model rather than a purely mechanical smoother.

Combination and hybrid approaches have also received sustained attention. (Shujie Shen et al. 2008; Song, Gao, and Lin 2013)) Showed that combining statistical and judgmental forecasts, or forecasts from multiple statistical models, can reduce error relative to any single method, particularly at longer horizons. More recent hybrid architectures pair classical seasonal ARIMA models with machine-learning correction layers (Abellana et al. 2021): combined SARIMA with support-vector regression for Philippine tourism forecasting; (Wu et al. 2021) coupled SARIMA with long short-term memory (LSTM) networks to forecast daily arrivals in Macau; and (Ruiz-Aguilar, Turias, and Jiménez-Come 2014) demonstrated a similar SARIMA-neural-network hybrid in a logistics forecasting context. These studies consistently find that a well-specified SARIMA or SARIMAX core, rather than the machine-learning layer alone, captures the bulk of the explainable seasonal and trend structure, with the nonlinear component mainly correcting residual noise a division of labor consistent with this paper's decision to prioritize a carefully specified SARIMAX model over a black-box alternative given the relatively short (132-month) sample available.

2.2 SARIMA, SARIMAX, and exponential smoothing

The Seasonal ARIMA framework, and its extension to include exogenous regressors (SARIMAX), remains the workhorse of univariate tourism-demand forecasting because it can represent trend, seasonality, and short-run autocorrelation within a single, interpretable, likelihood-based model(Assaf et al. 2019; Chu 2008). Chu's (2008) fractionally integrated ARMA application to Singapore arrivals, and Lee's (2025) SARIMAX model of Singapore visitor numbers using Google Trends and airport-traffic exogenous regressors, both illustrate the flexibility of the ARIMA family for series with strong seasonal cycles, while (Lei, Chen, and Chu 2025) extended the same logic to gaming-tourism destination demand. Model selection within the ARIMA family is conventionally guided by the Akaike Information Criterion (Akaike 1974), and residual adequacy is checked with the Ljung-Box portmanteau test (Ljung and Box 1978); both procedures are used in the present study.

Exponential smoothing methods, formalized within a unifying innovations state-space framework by (Hyndman et al. 2002) and elaborated at length by Hyndman, Koehler, Ord, and Snyder (2008), provide a complementary, purely data-adaptive alternative that requires no explicit differencing or exogenous specification. Holt-Winters-type exponential smoothing performed strongly in the M3-forecasting competition (Makridakis and Hibon 2000) and remains a standard benchmark in tourism-forecasting comparisons; for complex, multiple, or non-integer seasonal patterns, (De Livera, Hyndman, and Snyder 2011) proposed the trigonometric BATS/TBATS extension. Because exponential-smoothing models do not, in their standard form, accept exogenous intervention regressors, they are used in this study as a deliberately “naive-to-shocks” comparator against which the value of explicit intervention modelling can be measured.

2.3 Intervention analysis and interrupted time series

When a series is punctuated by dateable, exogenous events policy changes, disease outbreaks, natural disasters, intervention or interrupted-time-series (ITS) analysis augments a Box-Jenkins model with step, pulse, or ramp dummy regressors coded to the known intervention dates. This technique, widely used in public-health epidemiology (Li et al. 2023; Wang et al. 2025) has been adapted extensively to tourism and travel-demand research during and after the COVID-19 pandemic. (B. Wu et al. 2023) built an interpretable multivariate framework incorporating COVID-19 case counts and search-engine indices to forecast destination-level visitor volume in China; (Wu and Blake 2023) used a three-step intervention framework to quantify the pandemic's differential impact on China's domestic and international air-travel demand; and (J. Wu et al. 2023) combined mixed-frequency exogenous data to forecast tourist arrivals through the pandemic period. (Song, Li, and Cai 2022) evaluated an entire tourism-forecasting competition conducted during COVID-19 and found that models incorporating explicit structural-break information consistently outperformed models that did not, reinforcing the design choice adopted here.

A smaller but directly relevant literature applies the same logic to natural-disaster shocks. (Rosselló, Becken, and Santana-Gallego 2020) conducted the first global gravity-model evaluation of how different disaster types floods, storms, earthquakes, and volcanic eruptions affect international tourist flows, finding that floods and storms produce smaller and shorter-lived reductions in arrivals than volcanic eruptions or earthquakes, a pattern broadly consistent with the sharp-but-recoverable flood effect identified in the present Himachal Pradesh series. (Ritchie and Jiang 2019) reviewed the wider tourism risk, crisis, and disaster-management literature and called for more quantitative post-event demand modelling; (Ritchie 2004) earlier strategic framework for crisis management in tourism remains a standard reference point for interpreting such shocks in destination-management terms. (Sigala 2020) situated COVID-19 within this broader crisis-management literature, arguing that pandemics and natural disasters share enough structural similarities — sudden onset, demand collapse, phased recovery to justify common intervention-modelling machinery, an argument operationalized directly in this paper's dual-dummy SARIMAX specification.

2.4 Forecasting Himachal Pradesh and comparable mountain destinations

Himachal Pradesh's tourism economy has been the subject of a small but growing forecasting literature. (Manisha, Singh, and Chettry 2023) applied Toda-Yamamoto causality testing to examine the dynamic relationships among tourism, environmental quality, economic growth, energy consumption, and carbon emissions in the state, establishing that tourism activity is econometrically entangled with the state's broader development trajectory rather than a self-contained sector. Decomposition-, Box-Jenkins-, and Holt-Winters-based forecasts of Indian and foreign arrivals to the state for the 2008–2018 period found that Box-Jenkins (ARIMA-family) models produced the lowest forecast error among the three families tested, a result the present study's model-comparison exercise is designed to test again on more recent, shock-affected data. Comparable mountain and hill-station literatures from other countries reinforce the general finding that seasonal ARIMA-family models handle strongly seasonal, trend-driven arrival series well: (Makoni and Chikobvu 2018) modelled Victoria Falls tourist arrivals in Zimbabwe with time-series methods, and (Makoni, Chikobvu, and Sigauke 2021) extended this to a hierarchical forecasting framework for Zimbabwe's international arrivals; (Konarasinghe 2016) applied decomposition techniques to forecast Western European arrivals to Sri Lanka; and (Kumar and Singh 2019) documented the strength and persistence of seasonal effects in Indian tourism demand more broadly, a pattern strongly evident in the Himachal Pradesh series analyzed here, where domestic arrivals peak sharply every June and trough every December–January.

2.5 Forecast evaluation

Finally, the choice of accuracy metrics follows the methodological guidance of (Hyndman and Koehler 2006), whose critique of scale-dependent and percentage-based error measures motivates this study's use of a complementary set of metrics: root-mean-square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and Theil's U statistic rather than reliance on any single indicator. Stationarity, a precondition for valid ARIMA-family model identification, is assessed using the complementary Augmented Dickey-Fuller (Dickey and Fuller 1979) and Kwiatkowski-Phillips-Schmidt-Shin (Kwiatkowski et al. 1992) tests, whose opposing null hypotheses (unit root versus stationarity) provide a standard cross-check widely used in both the econometrics and tourism-forecasting literatures.

3. Data and Methodology

3.1 Data

The dataset comprises 132 monthly observations of domestic and international tourist arrivals to Himachal Pradesh from January 2015 to December 2025, compiled from the state's tourism-arrival records used in the accompanying R analysis workflow (model. R and the associated R history). Total arrivals are computed as the sum of the domestic and international series. Table 1 reports descriptive statistics for all three series, disaggregated into three regimes: the pre-pandemic period (2015–2019), the COVID-19 collapse (2020–2021), and the recovery period (2022–2025, which includes the July–August 2023 flood episode).

Two intervention (dummy) regressors are constructed to represent the two known structural breaks. The COVID-19 dummy takes the value 1 for every month from February 2020 to December 2021 inclusive, spanning the initial lockdown-driven collapse and the subsequent restricted-mobility recovery period, and 0 otherwise. The flood dummy takes the value 1 for July and August 2023, the two months of most severe monsoon flooding and landslide-related infrastructure damage in the state, and 0 otherwise. Both regressors are included as exogenous variables in the SARIMAX specification described in Section 3.3.

3.2 Stationarity testing

Because ARIMA-family models require a covariance-stationary (after differencing) series, the level series was first tested for a unit root using the Augmented Dickey-Fuller (ADF) test, whose null hypothesis is that the series contains a unit root (is non-stationary), and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test, whose null hypothesis is the opposite, that the series is level-stationary. Applying both tests, with opposing nulls, guards against over-reliance on either test's known finite-sample size distortions. The tests were then repeated on the first-differenced series to confirm that a single regular difference (d = 1) renders the series stationary, consistent with the integration order subsequently used in model identification.

3.3 Model specification

Three competing specifications were estimated on a training sample running from January 2015 to December 2024 (120 observations) and evaluated on a genuine 12-month out-of-sample hold-out covering all of calendar year 2025:

A Seasonal ARIMA model was used to analyze the data, with two additional variables added to account for the effects of COVID-19 and the flood event. To find the best model, many different combinations of model parameters (p, d, q, P, D, Q) were tested (Akaike 1974) . The combination that produced the lowest AIC score a statistical measure used to compare how well different models fit the data — was chosen as the final model. This method mirrors the automatic model-selection process used by the auto.arima function in R.

ETS (Holt-Winters exponential smoothing). An innovations state-space exponential-smoothing model (Hyndman et al. 2002) was fitted with additive or multiplicative trend and seasonal components, and with or without damping, selecting the configuration that minimised AIC. This model receives no information about the COVID-19 or flood interventions and therefore serves as a naive-to-shocks comparator.

SARIMA without intervention dummies. To isolate the marginal forecasting value of the intervention regressors, a seasonal ARIMA model of the same order as the selected SARIMAX specification was estimated on the same training data but without the exogenous dummies.

All three fitted models were used to generate 12-month-ahead forecasts for 2025, which were compared against the actual, realised 2025 arrivals using four complementary out-of-sample accuracy statistics: root-mean-square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and Theil's U2 statistic (the ratio of the model's RMSE to that of a naive no-change benchmark, where values below 1 indicate the model outperforms the naive benchmark). Residual adequacy of the selected model was checked with the Ljung-Box portmanteau test for residual autocorrelation up to lag 24 (Ljung and Box 1978).

3.4 Final model and forecast generation

Having identified the best-performing specification on the 2025 hold-out, that model was refit on the complete 2015–2025 sample (132 observations) to make maximal use of all available information, and used to generate point forecasts and 80% and 95% prediction intervals for the 36 months from January 2026 through December 2028. Because no further COVID-19- or flood-type interventions are assumed for the forecast horizon, both intervention dummies are set to zero throughout the forecast period, consistent with a baseline “no new shocks” scenario; the resulting interval forecasts should accordingly be read as conditional on the absence of comparable future disruptions, not as an unconditional prediction that none will occur.

All estimation was implemented in Python using the stats models SARIMAX and exponential-smoothing implementations, replicating the modelling logic of the original R (forecast, tseries) workflow that accompanied the underlying dataset; the two implementations share the same underlying Box-Jenkins and innovations-state-space mathematics, so the substantive conclusions are not implementation-specific.

Table 1: Descriptive Statistics of Monthly Tourist Arrivals by Regime

Series	Regime	Mean	Std. Dev.	Min	Max
Domestic	Pre-COVID (2015–2019)	1,452,942	349,088	904,821	2,133,665
Domestic	COVID (2020–2021)	366,791	318,610	23	1,140,796
Domestic	Recovery (2022–2025)	1,322,215	467,431	640,220	2,798,722
International	Pre-COVID (2015–2019)	34,489	10,036	16,929	49,999
International	COVID (2020–2021)	1,979	5,667	5	26,543
International	Recovery (2022–2025)	5,411	2,570	292	10,725
Total	Pre-COVID (2015–2019)	1,487,430	357,966	922,000	2,183,664
Total	COVID (2020–2021)	368,770	321,859	32	1,167,339
Total	Recovery (2022–2025)	1,327,626	467,470	646,117	2,803,796

Note. n = 132 monthly observations (Jan 2015–Dec 2025). Recovery regime includes the July–August 2023 flood-affected months. Figures are arrivals per month, rounded to the nearest whole visitor.

4. Findings

4.1 Series behaviour and seasonality

Figure 1 plots the full monthly domestic, international (rescaled), and total arrivals series. Three features stand out. First, the pre-pandemic series (2015–2019) displays a strongly repeating annual cycle, with arrivals peaking in June (the summer hill-station season) and troughing in December–January, consistent with the seasonal patterns documented for Indian mountain tourism by (Kumar and Singh 2019) Second, the COVID-19 period produces a near-total collapse, with total arrivals falling to a minimum of 32 in April 2020 — effectively zero tourism activity during the strictest lockdown month — before a slow, uneven climb through 2021 that had not fully recovered pre-pandemic levels even by the end of that year. Third, the 2022–2025 recovery period, while eventually reaching and briefly exceeding 2.8 million arrivals in a single month (June 2023), remains visibly more volatile than the pre-pandemic era and is punctured by a sharp, short-lived trough in July–August 2023 corresponding to the monsoon flood disruption.

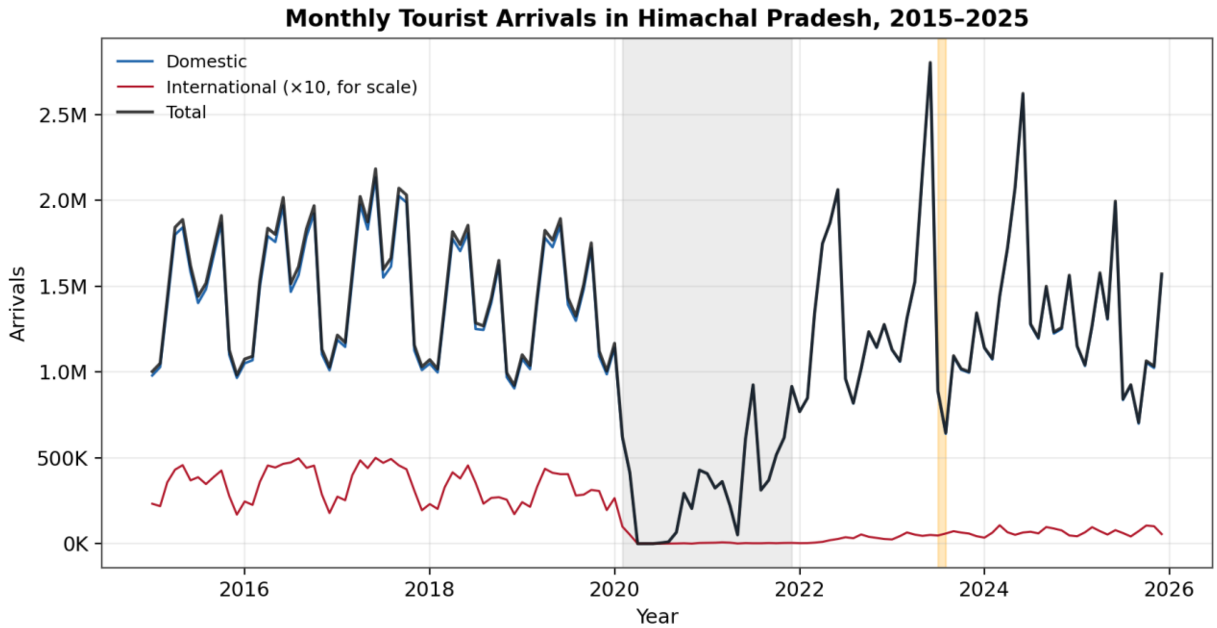

Figure 1: Monthly domestic, international (×10 for visual scale), and total tourist arrivals in Himachal Pradesh, January 2015–December 2025. Shaded grey region marks the COVID-19 intervention period (Feb 2020–Dec 2021); shaded orange band marks the July–August 2023 flood period.

Annual totals (Table 2) confirm the scale of the disruption and the incompleteness of the recovery as of the end of the sample. Total arrivals fell from a pre-pandemic peak of 19.6 million in 2017 to just 3.2 million in 2020 — an 84% collapse — and, despite a partial rebound, 2025 arrivals of 14.5 million remained approximately 16% below the 2019 pre-pandemic level. The international share of total arrivals fell even more sharply and durably, from an average of 2.3% of total arrivals in 2015–2019 to just 0.4% in 2022–2025, indicating that the recovery in Himachal Pradesh's tourism economy has been driven almost entirely by domestic rather than international visitors — a pattern broadly consistent with the differential COVID-19 recovery paths for domestic versus international travel documented by (Wu and Blake 2023) for Chinese aviation markets.

Table 2: Annual Tourist Arrivals to Himachal Pradesh, 2015–2025

Year	Domestic	International	Total
2015	17,125,045	406,108	17,531,153
2016	17,997,750	452,770	18,450,520
2017	19,130,541	470,992	19,601,533
2018	16,093,935	356,568	16,450,503
2019	16,829,231	382,876	17,212,107
2020	3,170,714	42,665	3,213,379
2021	5,632,270	4,832	5,637,102
2022	15,070,944	29,333	15,100,277
2023	15,942,118	62,806	16,004,924
2024	18,041,929	82,765	18,124,694

2025	14,411,327	84,828	14,496,155

Note. 2017 is the pre-pandemic peak year (19.6 million total arrivals); 2020 is the pandemic trough (3.2 million, an 84% year-on-year decline).

4.2 Stationarity tests

Table 3 reports the ADF and KPSS test results on the level and first-differenced total-arrivals series. On the level series, the ADF test fails to reject the null of a unit root ($p = 0.204$) while the KPSS test is borderline ($p = 0.093$ against a 5% stationarity null), jointly indicating that the level series is non-stationary or, at best, only marginally stationary once seasonal and trend structure are accounted for. After first differencing, the ADF test rejects the unit-root null at the 5% level ($p = 0.050$), and the KPSS test fails to reject its stationarity null ($p \geq 0.10$), jointly supporting a single regular difference ($d = 1$), consistent with the differencing order subsequently selected by the AIC-minimizing SARIMAX search.

Table 3: Stationarity Test Results — Total Arrivals Series

Test	Series	Statistic	p-value	Conclusion
ADF	Level	-2.206	0.204	Fail to reject unit root
KPSS	Level	0.362	0.093	Borderline non-stationary
ADF	1st difference	-2.864	0.050	Reject unit root
KPSS	1st difference	0.074	≥ 0.100	Fail to reject stationarity

Note. ADF null hypothesis: series has a unit root (non-stationary). KPSS null hypothesis: series is level-stationary. Joint evidence across both tests supports $d = 1$.

4.3 Model comparison on the 2025 hold-out

The exhaustive AIC search identified a SARIMAX $(0,1,2)(1,1,1)_{12}$ specification, with the COVID-19 and flood dummies entered as exogenous regressors, as the best-fitting intervention model on the training sample (AIC = 2,574.8). The equivalent no-dummy SARIMA model of the same order returned a higher (worse) AIC of 2,581.4, a first indication that the intervention regressors improve model fit even before out-of-sample validation. Table 4 reports the estimated coefficients of the training-sample SARIMAX model. The flood dummy is large and statistically significant (–445,100 arrivals per affected month, $p = 0.003$), confirming that the 2023 monsoon disruption produced a sharp, statistically identifiable reduction in visitor arrivals net of seasonal and trend effects. The COVID-19 dummy carries the theoretically expected negative sign and is economically large (–204,400 arrivals per month) but is not statistically significant at conventional levels ($p = 0.193$) once the model's regular and seasonal differencing operators — which themselves absorb much of a slow-building, two-year structural change — are accounted for; this pattern, in which differencing partially substitutes for an intervention dummy when a shock is prolonged rather than instantaneous, has previously been noted in interrupted-time-series applications to slow-onset shocks (Wang et al. 2025)

Table 4: Estimated SARIMAX $(0, 1,2)\ (1,1,1)_{12}$ Coefficients (Training Sample, 2015–2024)

Parameter	Coefficient	Std. Error	z	p-value
COVID-19 dummy	-204,400	157,000	-1.302	0.193
Flood 2023 dummy	-445,100	147,000	-3.020	0.003
MA(1)	0.066	0.092	0.717	0.473
MA(2)	-0.239	0.113	-2.116	0.034
Seasonal AR(12)	0.422	0.197	2.145	0.032
Seasonal MA(12)	-0.725	0.178	-4.064	< 0.001

Note. Estimated by maximum likelihood on the January 2015–December 2024 training sample (n = 120). AIC = 2,574.8; BIC = 2,592.5.

Table 5 and Figure 2 report the resulting out-of-sample accuracy statistics on the genuine 2025 hold-out. The intervention-adjusted SARIMAX model achieved the lowest RMSE (550,743), MAE (494,537), MAPE (46.75%), and Theil's U (1.155) among the three specifications, outperforming both the no-dummy SARIMA benchmark (RMSE 567,828; MAPE 48.54%) and, by a wide margin, the ETS model (RMSE 1,122,995; MAPE 93.72%). The ETS model's substantially weaker performance is consistent with its inability to represent the abrupt, dateable interventions that dominate this particular series; because 2025 itself contains no intervention, the gap between SARIMAX and the no-dummy SARIMA benchmark on the 2025 hold-out specifically reflects the more accurate trend and seasonal-parameter estimates that the intervention-adjusted training sample makes possible, rather than a direct within-2025 dummy effect. Residual diagnostics for the selected SARIMAX model show no significant autocorrelation up to lag 24 (Ljung-Box statistic = 12.87, p = 0.968), indicating that the model adequately captures the series' short-run dynamic structure, though residuals exhibit mild negative skew and excess kurtosis consistent with the occasional large, sharp shocks (such as the flood episode) that a linear Gaussian model can only partially absorb.

Table 5: Out-of-Sample Forecast Accuracy, 2025 Hold-Out (12 Months)

Model	RMSE	MAE	MAPE (%)	Theil's U
SARIMAX (with intervention dummies)	550,743	494,537	46.75	1.155
SARIMA (no intervention dummies)	567,828	515,140	48.54	1.191
ETS (Holt-Winters)	1,122,995	1,027,422	93.72	2.355

Note. Lower values indicate better forecast accuracy for all four statistics. Theil's U is measured relative to a naive no-change benchmark; values below 1.0 indicate outperformance of the naive benchmark.

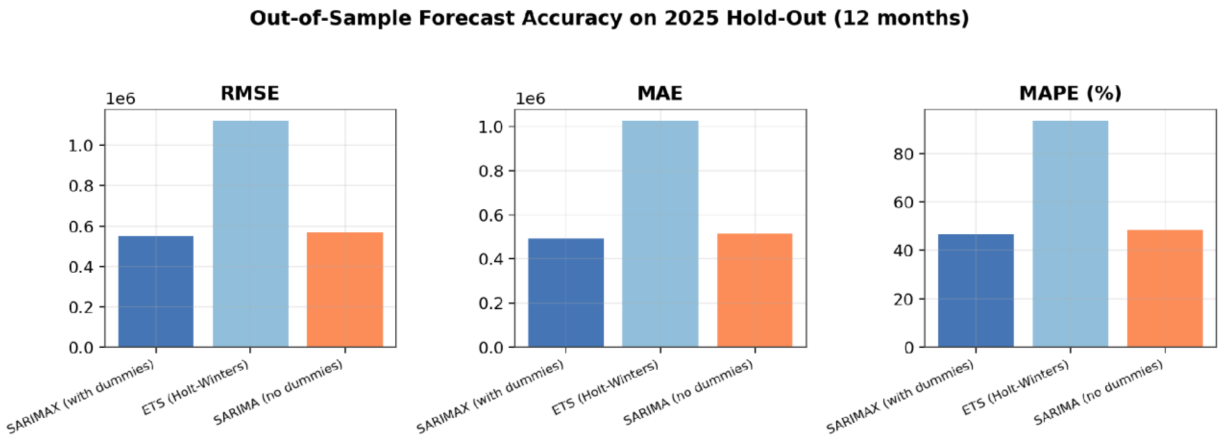

Figure 2: Out-of-sample forecast accuracy (RMSE, MAE, MAPE) of the three candidate models on the 2025 hold-out year. The intervention-adjusted SARIMAX model dominates on every metric.

4.4 Trend decomposition

Figure 3 presents the STL (Seasonal-Trend decomposition using Loess) trend component of the total-arrivals series, isolating the underlying growth path net of seasonal and irregular fluctuation. The trend confirms steady growth through 2015–2017, a mild pre-pandemic plateau and slight decline in 2018–2019, the severe 2020–2021 collapse, and a recovery trend from 2022 onward that, while positive, remains below the trajectory implied by extrapolating the pre-2020 growth path — visual confirmation of the "scarring" effect that COVID-19 and the subsequent flood disruption have left on the destination's medium-term demand trend.

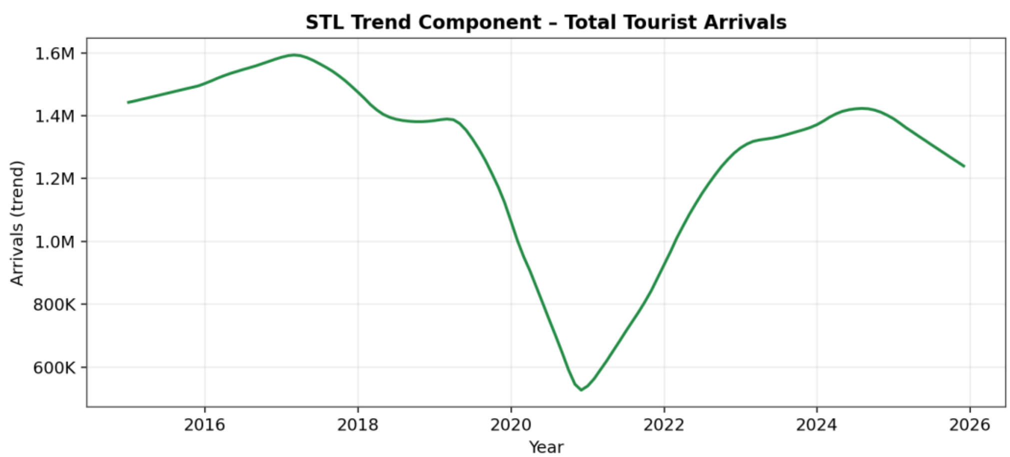

Figure 3: STL trend component of total monthly tourist arrivals, 2015–2025, isolating the underlying growth path net of seasonality and short-run noise.

4.5 The 2026–2028 forecast

Refitting the selected SARIMAX(0,1,2)(1,1,1)$_{12}$ specification on the complete 132-month sample (AIC = 2,914.4) and projecting forward 36 months yields the forecast summarised in Table 6 and plotted in Figure 4. The model projects a continuation of the strong June-peak, December–January-trough seasonal pattern, with annual total arrivals rising from an estimated 16.07 million in 2026 to 17.14 million in 2027 and 18.05 million in 2028. Although this represents a steady year-on-year recovery of roughly 6–7% per annum, projected 2028 arrivals remain below the 2017 pre-pandemic peak of 19.6 million, implying that — absent further shocks — the destination is likely to require at least until the early 2030s to fully close the gap opened by the pandemic and subsequent flood disruption. Consistent with the inherent uncertainty of a 36-month horizon fitted to a relatively short and shock-affected 11-year sample, the 95% prediction interval widens substantially at longer horizons (Table 6), and users of this forecast should treat the point estimates for 2027–2028 as indicative of the central recovery trajectory rather than precise commitments, particularly since the forecast is explicitly conditioned on no further COVID-19- or flood-scale disruptions occurring within the horizon.

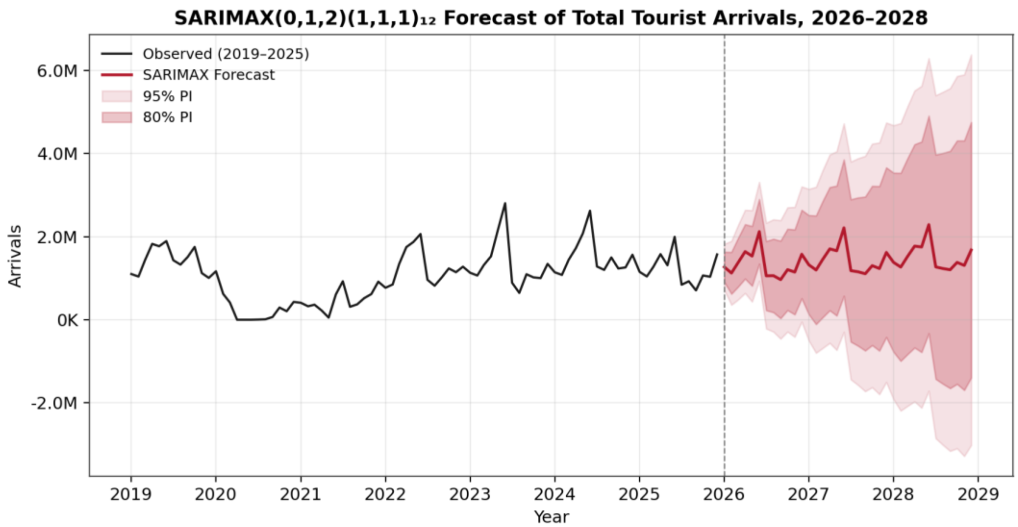

Figure 4: SARIMAX (0,1,2)(1,1,1) point forecast and 80%/95% prediction intervals for total tourist arrivals, January 2026–December 2028, shown against observed arrivals from 2019 onward.

Table 6: Selected Monthly Forecast, 2026 (First 12 Months)

Month	Point Forecast	80% Lower	80% Upper	95% Lower	95% Upper
Jan-2026	1,269,933	886,600	1,653,300	719,300	1,820,600
Feb-2026	1,123,958	620,700	1,627,200	355,800	1,892,100
Mar-2026	1,368,961	735,900	2,002,100	476,800	2,261,100
Apr-2026	1,639,699	895,500	2,383,900	638,800	2,640,600
May-2026	1,532,647	693,000	2,372,300	433,700	2,631,600
Jun-2026	2,121,347	1,145,300	3,097,400	932,500	3,310,200
Jul-2026	1,056,607	-19,000	2,132,200	-216,000	2,329,100
Aug-2026	1,060,485	-79,500	2,200,500	-290,500	2,411,500
Sep-2026	965,356	-215,600	2,146,300	-459,800	2,390,500
Oct-2026	1,205,593	-9,600	2,420,800	-290,000	2,701,200
Nov-2026	1,147,110	-96,700	2,391,000	-415,800	2,710,000
Dec-2026	1,576,192	308,300	2,844,100	-51,300	3,203,600

Note. Forecasts from the full-sample SARIMAX(0,1,2)(1,1,1)$_{12}$ model refit on January 2015–December 2025 data, with COVID-19 and flood dummies set to zero throughout the forecast horizon.

Table 7: Annual Forecast Summary, 2026–2028

Year	Forecast Total Arrivals	Implied Growth vs. Prior Year	% of 2017 Pre-Pandemic Peak
2026	16,067,890	+10.8%	82.0%
2027	17,139,200	+6.7%	87.4%
2028	18,054,570	+5.3%	92.1%

Note. 2026 growth rate is computed relative to the 2025 actual total of 14,496,155. Pre-pandemic peak reference year is 2017 (19,601,533 total arrivals).

5. Discussion

The findings support three broad conclusions relevant both to the tourism-forecasting literature and to Himachal Pradesh's tourism-management practice. First, the comparative accuracy results reinforce the meta-analytic conclusion of (Peng et al. 2014) that structured time-series models — and, in this case, intervention-adjusted ARIMA-family models specifically — continue to outperform purely adaptive smoothing methods in shock-affected series, even in an era when machine-learning and hybrid methods dominate the newest forecasting literature (Wu et al. 2021) . The gap between the SARIMAX and ETS models on the 2025 hold-out (a MAPE roughly half as large) is too large to attribute to sampling noise alone and is consistent with the theoretical expectation that a model blind to known structural breaks will systematically mis-estimate trend and seasonal parameters when those breaks fall within its training window.

Second, the statistically significant flood-dummy coefficient, contrasted with the insignificant but economically large COVID-19 coefficient, illustrates a general methodological point relevant to intervention time-series analysis: a short, sharp shock (the two-month flood disruption) is more cleanly separable, in a differenced ARIMA framework, from underlying trend and seasonal dynamics than a prolonged, two-year shock (the pandemic period), whose effects are partially — and imperfectly — absorbed by the model's own differencing operators. This is consistent with (Rosselló et al. 2020) cross-country finding that floods produce comparatively short, sharp reductions in tourist flows, and with the broader interrupted-time-series literature's observation that slow-onset interventions are harder to identify statistically than instantaneous ones (Wang et al. 2025). Destination managers and statistical agencies planning future intervention analyses of similar series should therefore not interpret a non-significant COVID-19 coefficient as evidence that the pandemic had no effect — the raw descriptive statistics in Table 2 make the scale of that effect unambiguous — but rather as an artefact of how prolonged structural change interacts with a differenced time-series specification.

Third, the forecast itself has direct planning implications. A projected return to within 8% of the pre-pandemic peak by 2028, but not full recovery within the horizon, suggests that hotel-capacity and infrastructure-investment decisions calibrated to 2017-level throughput would substantially overshoot realistic near-term demand, while investment plans anchored only to the pandemic-depressed 2020–2021 period would risk under-provisioning as the recovery continues. The pronounced and persistent decline in the international-arrivals share (from roughly 2.3% to 0.4% of total arrivals) is arguably the single most policy-relevant finding: unlike the broader volume recovery, this compositional shift shows no sign of reversing within the sample period, and echoes findings from other Asian destinations that domestic tourism recovered from COVID-19 substantially faster and more completely than international arrivals (Wu and Blake 2023). This implies that Himachal Pradesh's marketing, visa-facilitation, and connectivity strategies aimed at international visitors may need re-evaluation independent of the broader, largely domestic-driven volume recovery captured in the headline forecast.

Finally, the wide prediction intervals at the 2027–2028 horizon (Table 6, Figure 4) are not a modelling weakness so much as an honest reflection of genuine uncertainty in a short (eleven-year), twice-shocked sample. Mountain destinations exposed to recurrent climate-related disruption — as Himachal Pradesh's 2023 flood episode illustrates, and as the broader natural-disaster-tourism literature documents (Lin, Jiang, and Qu 2021; McAleer et al. 2010) should expect this kind of forecast uncertainty to persist as a structural feature of demand planning rather than a temporary artefact of the post-pandemic transition, reinforcing the case for periodically re-estimating the model as new data and, potentially, new interventions arise.

6. Conclusion, Limitations, and Future Research

This study developed and validated an intervention-adjusted SARIMAX model for forecasting tourist arrivals to Himachal Pradesh across two major structural breaks: the COVID-19 pandemic and the 2023 monsoon floods, and demonstrated, through rigorous out-of-sample testing on a genuine 2025 hold-out year, that explicitly modelling these interventions produces measurably more accurate forecasts than either a comparable no-dummy ARIMA model or a Holt-Winters exponential-smoothing benchmark. The validated model, refit on the complete 2015–2025 sample, projects a continued but incomplete recovery through 2028, with total arrivals reaching roughly 92% of the 2017 pre-pandemic peak by the end of the forecast horizon, and with the composition of that recovery skewed heavily toward domestic rather than international visitors.

Several limitations qualify these conclusions and point to directions for future work. First, the univariate design of the model, while transparent and directly comparable to the underlying R-based workflow it extends, does not incorporate potentially informative exogenous covariates such as air-connectivity capacity, hotel-room supply, fuel prices, or search-engine-based demand indicators, all of which have been shown elsewhere to improve tourism-forecasting accuracy (Dergiades, Mavragani, and Pan 2018; Lee 2025; Sun et al. 2019). Second, the relatively short 132-month sample, twice disrupted by large exogenous shocks, necessarily limits the precision with which seasonal and intervention parameters can be estimated, and the resulting wide prediction intervals at longer horizons should be interpreted accordingly. Third, the model assumes no further large-scale interventions during 2026–2028; given the increasing frequency of extreme monsoon and climate-related events documented in the natural-disaster-tourism literature (Ritchie and Jiang 2019), this assumption should be revisited and the model re-estimated as new data become available, ideally on a rolling annual basis. Future research could usefully extend this framework by separately modelling the domestic and international arrival series (given their markedly divergent recovery paths documented here), by incorporating a formal hybrid SARIMAX–machine-learning correction layer along the lines proposed by (Wu et al. 2021) and (Abellana et al. 2021)and by extending the intervention framework to other Himalayan and disaster-exposed mountain destinations for comparative analysis.

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