IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 15, No. 4, August 2026, pp. 3421~3430
ISSN: 2252-8938, DOI: 10.11591/ijai.v15.i4.pp3421-3430

Computational framework for smart tourism management: hybrid time series decomposition and predictive modeling

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Article Info

Article history:

Received Mar 28, 2025
Revised May 20, 2026
Accepted Jun 19, 2026

Keywords:

Predictive analytics
Rural tourism forecasting
Smart tourism
Sustainable development goals
Time-series decomposition

ABSTRACT

Smart tourism management in rural multi-destination settings requires forecasting methods that are accurate enough to support visitor allocation, infrastructure readiness, and ecological protection. This study presents a decomposition-based forecasting framework for Sidowayah Village, Central Java, Indonesia, which integrates three attractions with different demand profiles: Umbul Manten, Siblarak, and Kampung Dolanan. Using monthly visitation data from May 2023 to April 2024, the study compares additive and multiplicative decomposition models within a common workflow of data collection, preprocessing, trend-seasonal decomposition, model evaluation, and sustainability-oriented interpretation. The contribution of the study lies in clarifying destination-specific criteria for selecting additive versus multiplicative models, improving methodological transparency in preprocessing and temporal validation, and translating forecast outputs into practical smart tourism actions aligned with sustainable development goals (SDGs) 11 and 12. The results show that the multiplicative-average all model yields the lowest mean absolute percentage error (MAPE) for Umbul Manten (14.1%) and Siblarak (56.8%), while the additive-centered moving average model is more suitable for Kampung Dolanan based on mean absolute deviation (MAD) (162.6). Although the 12-month dataset limits long-term generalization, the framework provides a reproducible basis for data-informed tourism management in rural destinations.

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1. INTRODUCTION

Rural tourism destinations increasingly require evidence-based management because visitor growth, environmental carrying capacity, and local cultural assets must be balanced within a single governance system [1], [2]. This challenge becomes more complex when a village manages several attractions simultaneously, each with different demand cycles, visitor segments, and operational constraints. Sidowayah Village in Central Java, Indonesia, illustrates this condition through an integrated tourism ecosystem comprising Umbul Manten (natural spring tourism), Siblarak (ecotourism and festival-based visitation), and Kampung Dolanan (cultural and educational tourism). These interconnected sites form an integrated ecosystem where visitor flows and resource demands are interdependent. Accurate forecasting is therefore essential for sustainable governance [2]–[4].

Forecasting methods such as autoregressive integrated moving average (ARIMA), seasonal autoregressive integrated moving average (SARIMA), and long short-term memory (LSTM) have been widely used in tourism demand prediction [5]–[8]. However, many studies focus on urban destinations, airports, or single attractions with longer data histories and more homogeneous seasonal structures [9], [10]. In rural clustered destinations, one attraction may follow relatively stable holiday-based demand, another may depend on event-driven surges, while another may fluctuate according to school visits or community programs. Under such conditions, a single forecasting form is often insufficient [11]. Time-series decomposition remains useful because it separates trend, seasonal, and irregular components in an interpretable manner [12]–[16]. The novelty of this study therefore lies not in decomposition itself, but in its use as a managerial decision framework for a rural multi-attraction tourism system characterized by limited data, destination-specific volatility, and explicit sustainability concerns.

The main contributions of this study are threefold: first, it proposes a clearer hybrid decomposition workflow for heterogeneous rural multi-destination tourism series. Second, it explains the operational rationale for selecting additive versus multiplicative decomposition according to destination behavior [17], [18]. Third, it translates forecast outputs into practical smart tourism actions aligned with sustainable development goals (SDGs) 11 and 12 [19], [20].

2. PROPOSED METHOD

2.1. Study area and data collection

This study examines tourist visitation dynamics in Sidowayah Village, Central Java, Indonesia, which comprises three complementary attractions: Umbul Manten, Siblarak, and Kampung Dolanan. The analysis uses monthly visitation data from May 2023 to April 2024 obtained from local tourism administrators. The dataset was organized to support comparative forecasting across attractions with different seasonal and volatility profiles while preserving the chronology required for time-series modeling.

2.2. Data preprocessing

A structured preprocessing workflow was used to improve consistency before decomposition. Missing observations were completed by linear interpolation only when adjacent values were available [21]. Potential outliers were identified using the interquartile range (IQR) rule and, when judged likely to distort the short monthly series, were replaced using a conservative median-based strategy [22]. For Kampung Dolanan, the August outlier (18 visitors) was replaced with the median (570), explaining its normalized value of 0.40. Min-max normalization to [0,1] harmonized scale variations across destinations [23], [24]. This decision was intended to stabilize decomposition rather than inflate demand. Visitor counts were then normalized to the [0,1] interval for cross-destination comparison, daily records were aggregated into monthly totals, and chronological order was preserved in YYYY-MM format [25], [26]. Alternative imputation schemes were not tested in the current study and are therefore acknowledged as a limitation.

2.3. Hybrid time series decomposition framework

To support forecasting in a heterogeneous rural tourism setting, this study applies a hybrid decomposition framework that combines additive and multiplicative formulations within a single workflow. The aim is to preserve interpretability while allowing the decomposition form to follow the observed behavior of each destination. Additive decomposition was assigned to destinations with relatively stable seasonal amplitudes, whereas multiplicative decomposition was used for destinations in which seasonal effects appeared proportional to the series level [27]–[30], as defined in (1).

$$yt = Tt + St + Rt \tag{1}$$

For additive decomposition, Tt denotes the trend component, St the seasonal component, and Rt the residual component. The trend was estimated using a centered moving average with a window size of k =3, while the seasonal component was derived from average monthly deviations. Conversely, multiplicative decomposition was applied to destinations with proportional seasonal variation, especially Siblarak, where festival periods create amplified demand spikes, as defined in (2). Under this formulation, the observed series is represented as the product of the trend, seasonal, and residual components.

$$yt = Tt \times St \times Rt \tag{2}$$

For multiplicative decomposition, the trend was also estimated using a centered moving average with k =3, while the seasonal factor was derived from relative monthly ratios around the estimated trend. This destination-specific strategy improves practical interpretability for tourism managers, but the present study does not yet include formal statistical tests for selecting decomposition type. Accordingly, the model choice should be understood as an empirical decision rule that remains open to refinement through future seasonal-strength and likelihood-based diagnostics.

2.4. Model evaluation

Model performance was evaluated using mean absolute deviation (MAD), mean absolute percentage error (MAPE), and root mean squared error (RMSE). These metrics were selected because they jointly describe absolute deviation, relative forecasting error, and sensitivity to large misses. MAD quantifies the average absolute deviation between predicted and observed values, providing a direct interpretation of typical forecasting error, as defined in (3).

$$MAD = \frac{1}{n}\sum_{t-1}^{n}|y - \tilde{y}| \tag{3}$$

MAPE expresses forecasting error in percentage terms, enabling comparison across destinations with different visitation scales, as defined in (4).

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{y-\tilde{y}}{y}\right| \times 10 \tag{4}$$

RMSE assigns greater weight to large errors and is therefore useful for identifying models that are sensitive to sharp seasonal shocks or irregular demand spikes, as defined in (5).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(yi - \hat{y})^2}{N}} \tag{5}$$

Together, these metrics provide a practical basis for model comparison in the current study.

2.5. Model validation and robustness testing

To assess generalizability within the limits of a short dataset, temporal cross-validation was implemented by training the model on May 2023 to December 2023 data and evaluating it on January 2024 to April 2024 data [31]. Residual behavior was then reviewed using autocorrelation function/partial autocorrelation function (ACF/PACF) inspection and Ljung-Box testing [32]. In addition, sensitivity analysis was conducted by varying the moving-average window size (k =3, 5, and 7) to examine the stability of the decomposition results.

2.6. Integration with smart tourism sustainability goals

The forecasting outputs were interpreted as decision-support inputs for smart tourism governance. In practical terms, projected peaks can inform visitor redistribution, temporary capacity control, staff allocation, and infrastructure readiness. In addition, forecast-informed off-peak programming can support more even demand distribution and reduce pressure on environmentally sensitive or operationally constrained sites. Through this interpretation, the framework links predictive analytics with sustainability-oriented tourism management aligned with SDGs 11 and 12 shows in Figure 1.

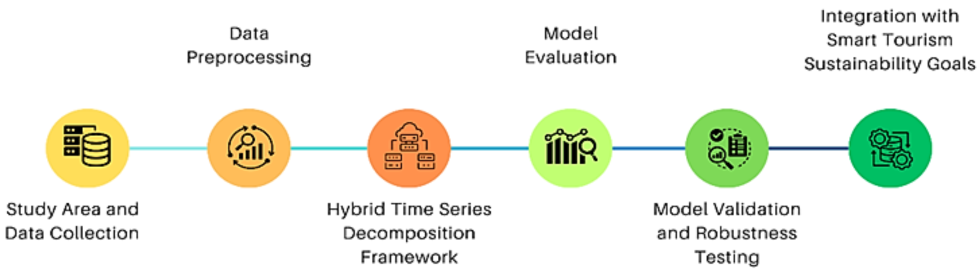

Figure 1. Workflow of the hybrid decomposition framework

3. RESULTS AND DISCUSSION

3.1. Study area, data collection, and data preprocessing

Table 1 and Figure 2 summarize the monthly visitation profiles of the three attractions and the preprocessing outputs used for modeling. Umbul Manten and Siblarak show clear year-end increases, with peak values recorded in December, while Kampung Dolanan exhibits substantially higher month-to-month instability. As shown in Table 1, peak visitation occurs in December at Umbul Manten (32,644 visitors) and Siblarak (18,746 visitors). Kampung Dolanan exhibits extreme fluctuations (ranging from 18 to 1,126 visitors monthly). The preprocessing steps included linear interpolation for missing values [21], IQR-based outlier detection and median replacement [22], min-max normalization [23], [24], monthly aggregation [25], [26], and chronological alignment to YYYY-MM format [33]. For Kampung Dolanan, August outlier (18 visitors) was replaced with the median of 570, which explains its normalized value of 0.40. The preprocessing stage therefore served not only a technical role but also an interpretive one by making the contrast between relatively stable and highly volatile destinations more visible before decomposition was applied.

Table 1. Tourist visits and data preprocessing

Month	Tourist visits			Preprocessed tourist visits		
	Umbul Manten	Siblarak	Kampung Dolanan	Umbul Manten (normalized)	Siblarak (normalized)	Kampung Dolanan (normalized)
May	12,000	3,000	832	0.00	0.03	0.71
June	20,412	7,166	1,110	0.41	0.29	1.00
July	22,199	6,547	514	0.50	0.25	0.40
August	20,176	2,468	18 (570)	0.40	0.00	0.40
September	19,173	6,064	700	0.35	0.22	0.58
October	20,361	9,688	562	0.41	0.44	0.44
November	21,094	9,633	1,126	0.44	0.44	1.00
December	32,644	18,746	912	1.00	1.00	0.79
January	24,921	6,513	412	0.63	0.25	0.30
February	12,732	4,358	570	0.04	0.12	0.45
March	18,635	4,507	406	0.32	0.13	0.29
April	19,918	3,125	113	0.38	0.04	0.00

3.2. Visual overview of destination visitation dynamics

Figure 2 provides a compact visual overview of the monthly visitation dynamics before full decomposition is examined. Two patterns are immediately visible: first, Umbul Manten and Siblarak both show clear increases toward the year-end holiday period. Second, Kampung Dolanan follows a more erratic path, with abrupt shifts that are less easily explained by simple seasonal regularity. This contrast supports the subsequent use of destination-specific decomposition logic.

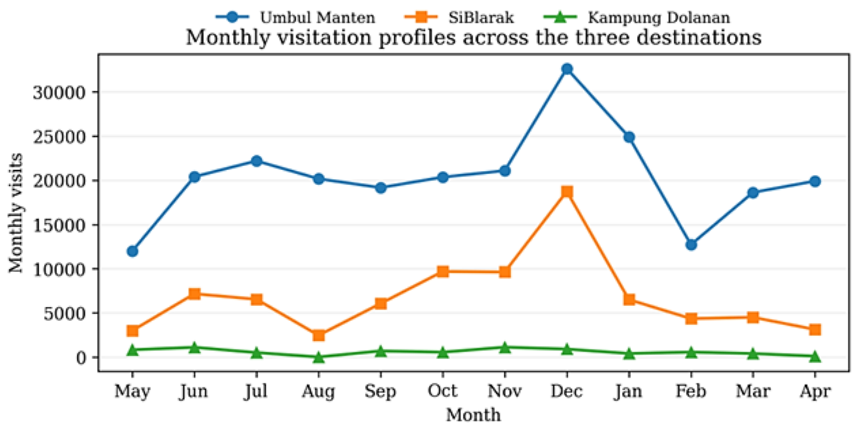

Figure 2. Monthly visitation profiles across the three destinations

3.3. Hybrid time series decomposition framework

This study presents a hybrid time-series decomposition framework that integrates additive and multiplicative models to capture diverse seasonal and trend behaviors across tourism destinations with heterogeneous demand characteristics [27]. Additive decomposition models absolute seasonal fluctuations around a stable mean. Multiplicative decomposition captures proportional variations that scale with demand levels.

3.3.1. Decomposed tourist visits for Umbul Manten

Table 2 presents the in-sample decomposition for Umbul Manten, which represents relatively stable natural tourism. The additive-centered moving average (MA) reveals short-term trend dynamics (ranging from 17,095 to 26,220 visitors). The additive-average all approach (with a mean of μ=20,355) highlights absolute seasonal deviations: a December peak (+12,289 visitors) and a February trough (−7,623 visitors). The multiplicative-average all model captures proportional variations: a 1.60 × increase in December and 0.63 × decrease in February. These findings are consistent with prior studies on multiplicative decomposition for proportional seasonal effects. The results support seasonal resource planning for staffing and facility capacity.

Table 2. Decomposed tourist visits for Umbul Manten

Month	Additive-centered MA			Additive-average all			Multiplicative-centered MA			Multiplicative-average all		
	Seasonal	Residual	Trend	Seasonal	Residual	Trend	Seasonal	Residual	Trend	Seasonal	Residual	Trend
May	-8,355	-	-	-	-	20,355	0.59	-	-	-	-	20,355
Jun	57	0	18,204	1.12	1.00	20,355	1.00	1.00	18,204	2,208	0	20,355
Jul	1,844	0	20,961	1.06	1.00	20,355	1.09	1.00	20,961	1,238	0	20,355
Aug	-179	0	20,516	0.98	1.00	20,355	0.99	1.00	20,516	-340	0	20,355
Sep	-1,182	0	19,903	0.96	1.00	20,355	0.94	1.00	19,903	-730	0	20,355
Oct	6	0	20,209	1.01	1.00	20,355	1.00	1.00	20,209	152	0	20,355
Nov	739	0	24,700	0.85	1.00	20,355	1.04	1.00	24,700	-3,606	0	20,355
Dec	12,289	0	26,220	1.25	1.00	20,355	1.60	1.00	26,220	6,424	0	20,355
Jan	4,566	0	23,432	1.06	1.00	20,355	1.22	1.00	23,432	1,489	0	20,355
Feb	-7,623	0	18,763	0.68	1.00	20,355	0.63	1.00	18,763	-6,031	0	20,355
Mar	-1,720	0	17,095	1.09	1.00	20,355	0.92	1.00	17,095	1,540	0	20,355
Apr	-437	0	-	-	-	20,355	0.98	1.00	-	-	-	20,355

3.3.2. Decomposed tourist visits for Siblarak

Table 3 presents the decomposition for Siblarak, which is characterized by event-driven ecotourism with higher volatility. Additive approaches capture absolute deviations: an August decline (−4,350 visitors) and a December peak (+11,928 visitors). Multiplicative models better represent proportional demand fluctuations. December reaches 2.75 × the annual mean, indicating that the impact of festivals scales with the destination's popularity. The multiplicative-centered MA model reveals local trend dynamics (ranging from 3,997 to 12,689 visitors) that global averaging smooths over. These findings suggest that multiplicative decomposition is more suitable for managing festival-driven demand surges. Additive models inform low-season mitigation strategies.

Table 3. Decomposed tourist visits for Siblarak

Month	Additive-centered MA			Additive-average all			Multiplicative-centered MA			Multiplicative-average all		
	Seasonal	Residual	Trend	Seasonal	Residual	Trend	Seasonal	Residual	Trend	Seasonal	Residual	Trend
May	-3,818	0	-	-	-	6,818	0.44	1.00	-	-	-	6,818
Jun	348	0	5,571	1.29	1.00	6,818	1.05	1.00	5,571	1,595	0	6,818
Jul	-271	0	5,394	1.21	1.00	6,818	0.96	1.00	5,394	1,153	0	6,818
Aug	-4,350	0	5,026	0.49	1.00	6,818	0.36	1.00	5,026	-2,558	0	6,818
Sep	-754	0	6,073	1.00	1.00	6,818	0.89	1.00	6,073	-9	0	6,818
Oct	2,870	0	8,462	1.15	1.00	6,818	1.42	1.00	8,462	1,226	0	6,818
Nov	2,815	0	12,689	0.76	1.00	6,818	1.41	1.00	12,689	-3,056	0	6,818
Dec	11,928	0	11,631	1.61	1.00	6,818	2.75	1.00	11,631	7,115	0	6,818
Jan	-305	0	9,872	0.66	1.00	6,818	0.96	1.00	9,872	-3,359	0	6,818
Feb	-2,460	0	5,126	0.85	1.00	6,818	0.64	1.00	5,126	-768	0	6,818
Mar	-2,311	0	3,997	1.13	1.00	6,818	0.66	1.00	3,997	510	0	6,818
Apr	-3,693	0	-	-	-	6,818	0.46	1.00	-	-	-	6,818

3.3.3. Decomposed tourist visits for Kampung Dolanan

Table 4 presents the decomposition for Kampung Dolanan, which exhibits extreme volatility due to its dependence on school activities and cultural events. The additive-centered MA model captures short-term absolute fluctuations. The trend peaks at 866.67 visitors (in November) and declines to 363.00 visitors (in March). Multiplicative models reveal dramatic proportional contrasts. November reaches 1.739 × the annual mean, while April plummets to 0.175 × the mean a tenfold difference. This reflects the strong seasonal concentration that is typical of educational tourism. Multiplicative decomposition better captures peak-period intensity. Additive models clarify low-season absolute magnitudes for targeted programming.

Table 4. Decomposed tourist visits for Kampung Dolanan

Month	Act	Additive-centered MA			Additive-average all			Multiplicative-centered MA			Multiplicative-average all		
		Seasonal	Residual	Trend	Seasonal	Residual	Trend	Seasonal	Residual	Trend	Seasonal	Residual	Trend
May	832	-3,818	0	-	-	-	6,818	0.44	1.00	-	-	-	6,818
Jun	1,110	348	0	5,571	1.29	1.00	6,818	1.05	1.00	5,571	1,595	0	6,818
Jul	514	-271	0	5,394	1.21	1.00	6,818	0.96	1.00	5,394	1,153	0	6,818
Aug	514	-4,350	0	5,026	0.49	1.00	6,818	0.36	1.00	5,026	-2,558	0	6,818
Sep	700	-754	0	6,073	1.00	1.00	6,818	0.89	1.00	6,073	-9	0	6,818
Oct	562	2,870	0	8,462	1.15	1.00	6,818	1.42	1.00	8,462	1,226	0	6,818
Nov	1,126	2,815	0	12,689	0.76	1.00	6,818	1.41	1.00	12,689	-3,056	0	6,818
Dec	912	11,928	0	11,631	1.61	1.00	6,818	2.75	1.00	11,631	7,115	0	6,818
Jan	412	-305	0	9,872	0.66	1.00	6,818	0.96	1.00	9,872	-3,359	0	6,818
Feb	570	-2,460	0	5,126	0.85	1.00	6,818	0.64	1.00	5,126	-768	0	6,818
Mar	406	-2,311	0	3,997	1.13	1.00	6,818	0.66	1.00	3,997	510	0	6,818
Apr	113	-3,693	0	-	-	-	6,818	0.46	1.00	-	-	-	6,818

3.4. Model evaluation for Umbul Manten, Siblarak, and Kampung Dolanan

Table 5 and Figure 3 compare the forecasting performance of the four decomposition configurations using MAD, MAPE, and RMSE. Figure 3 makes it easier to distinguish stable from unstable destinations by showing the relative error profile across models. The results show that the multiplicative-average all model achieves the lowest MAPE for Umbul Manten (14.1%) and Siblarak (56.8%), whereas the additive-centered MA model is more defensible for Kampung Dolanan because it yields the lowest MAD (162.6). Even so, the high MAPE values for Siblarak and Kampung Dolanan indicate that model fit remains constrained by volatility and data sparsity.

Table 5. Model performance comparison

Model	Umbul Manten			Siblarak			Kampung Dolanan		
	MAD	MAPE (%)	RMSE	MAD	MAPE (%)	RMSE	MAD	MAPE (%)	RMSE
Additive-centered MA	3,078	17.5	15,127,760	3,044	59.1	17,544,460	162.6	58.8	60,240
Additive-average all	2,706	14.4	11,037,820	2,978	58.5	17,535,310	153.3	165.0	30,162
Multiplicative-centered MA	2,907	16.9	13,190,120	2,974	56.8	17,783,470	191.7	157.8	65,343
Multiplicative-average all	2,633	14.1	10,571,970	2,981	56.8	17,554,320	197.6	158.4	59,567

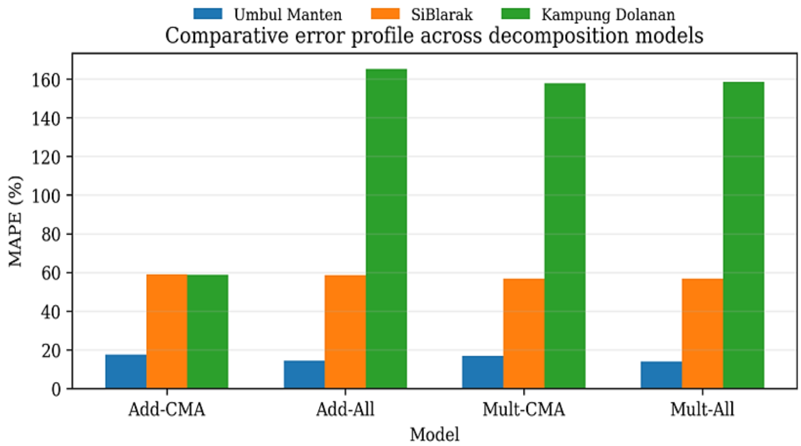

Figure 3. Comparative MAPE profile across decomposition models

3.5. Model validation and robustness analysis Umbul Manten, Siblarak, and Kampung Dolanan

Model validation and robustness checks were conducted through temporal cross-validation, residual diagnostics, and moving-window sensitivity analysis. Figure 4 complements Tables 6 to 8 by summarizing the generalization gaps and residual adequacy of the selected best-performing models. These results provide a concise overview of model performance and reliability.

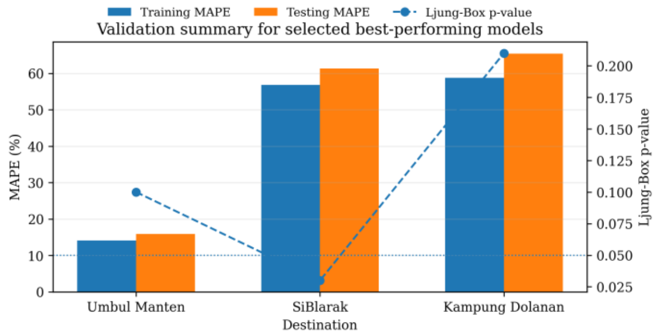

Figure 4. Validation summary for selected best-performing models

Table 6. Temporal cross-validation results and residual diagnostics

Destination	Model	Temporal cross-validation			Residual diagnostics	
		Training MAPE (%)	Testing MAPE (%)	ΔMAPE (%)	ACF/PACF randomness	Ljung-Box p-value
Umbul Manten	Additive-average all	14.4	16.2	+1.8	Yes	0.12
	Multiplicative-average all	14.1	15.9	+1.8	Yes	0.10
Siblarak	Multiplicative-average all	56.8	61.3	+4.5	No (ACF lag 1 0.45)	0.03
Kampung Dolanan	Additive-centered MA	58.8	65.4	+6.6	Yes	0.21

Table 7. Sensitivity of MAD to moving-average window size

Destination	Model	MAD (k =3)	MAD (k =5)	MAD (k =7)
Umbul Manten	Additive-centered MA	3,078	3,245	3,412
Siblarak	Multiplicative-centered MA	2,974	3,102	3,305
Kampung Dolanan	Additive-centered MA	162.6	178.9	195.3

Table 8. Benchmark performance based on MAPE

Destination	Decomposition model	Naïve baseline (%)	Improvement (%)
Umbul Manten	Multiplicative-average all	18.7	4.6
Siblarak	Multiplicative-average all	63.5	6.7
Kampung Dolanan	Additive-centered MA	67.2	8.4

3.5.1. Temporal cross-validation and residual diagnostics

Temporal cross-validation shows that Umbul Manten maintains relatively stable performance between the training and testing periods, whereas Siblarak and Kampung Dolanan experience larger error increases. This pattern suggests that demand in the latter two destinations is more strongly influenced by irregular factors that are not fully represented in the short historical series. Residual diagnostics support the same interpretation. Umbul Manten and Kampung Dolanan show comparatively random residual behavior, but Siblarak retains residual autocorrelation, indicating that event-related effects remain unmodeled. In practical terms, this means that festival calendars, weather variables, or promotional interventions should be incorporated in future forecasting extensions.

3.5.2. Sensitivity testing

The moving-window sensitivity analysis indicates that k =3 offers the best compromise between responsiveness and smoothness across the three destinations. Larger windows reduce short-term noise. However, they also delay trend adaptation and weaken the visibility of local seasonal changes.

3.5.3. Benchmark comparison

The benchmark analysis shows that the proposed decomposition configurations outperform naive forecasting across all destinations. Even so, this comparison should be interpreted cautiously because the current benchmark does not yet include ARIMA, SARIMA, or LSTM baselines. The main contribution at this stage is therefore analytical transparency rather than exhaustive model superiority. Figure 4 condenses the validation evidence reported in Tables 6 to 8. The comparison between training and testing MAPE shows that Umbul Manten generalizes more smoothly than the other destinations, while the lower Ljung-Box p-values and larger error gaps for Siblarak highlight unresolved structural volatility.

3.6. Integrated smart tourism framework for Sidowayah Village

The integrated framework emerging from these findings is best understood as a practical decision-support architecture rather than a fully automated prediction engine. It links data preparation, decomposition-based forecasting, model interpretation, and managerial response within a single tourism-governance workflow. Table 9 summarizes this translation by connecting forecast signals with recommended actions and SDG-linked implications. The framework is especially relevant for rural destinations that need simple but interpretable analytics under limited data conditions.

Table 9. Forecast signals, managerial actions, and SDG alignment

Forecast signal	Recommended managerial action	Primary destination implication	SDG linkage
Strong year-end demand surge	Activate staffing, parking, and temporary capacity controls	Umbul Manten and Siblarak	SDG 11: safer and more manageable visitor flows
Irregular volatility	Use flexible scheduling and small-batch resource allocation	Kampung Dolanan	SDG 12: more efficient resource use
Persistent residual dependence	Add event-calendar monitoring and manual review before peak periods	Siblarak	SDG 11 and 12: risk-aware operational planning
Low-season decline	Deploy targeted educational or cultural promotions	Kampung Dolanan and shoulder-season periods	SDG 12: balanced demand redistribution

3.7. Discussion

This study demonstrates that decomposition-based forecasting can support tourism decision-making in data-constrained rural settings, but its usefulness varies markedly across destinations. The strongest performance was observed for Umbul Manten, where seasonal demand was comparatively stable. Siblarak remained more difficult to model because festival-driven visitation produces irregular surges, while Kampung Dolanan exhibited high volatility likely associated with school-group scheduling and non-recurring community activities. These differences explain why a single model form is not equally suitable across all three sites. Accordingly, the present contribution should be read as a more transparent and decision-oriented decomposition framework rather than a final forecasting benchmark. It improves methodological clarity by making preprocessing choices, model-selection logic, and validation boundaries more explicit. At the same time, the study remains limited by its 12-month dataset, the absence of alternative imputation experiments, the lack of formal decomposition-selection tests, and the omission of stronger baselines such as ARIMA, SARIMA, or LSTM. Future work should address these gaps using longer series, richer exogenous variables, and hybrid or ensemble forecasting designs.

4. CONCLUSION

This study examined monthly tourist visitation patterns in Sidowayah Village using a hybrid decomposition framework designed for three integrated rural destinations: Umbul Manten, Siblarak, and Kampung Dolanan. The results show that destination-specific decomposition can support practical tourism planning when data are limited, but forecasting quality varies substantially across attraction types. Multiplicative decomposition is more suitable for Umbul Manten and Siblarak, whereas additive-centered decomposition is more defensible for Kampung Dolanan. The main value of the study lies in offering a transparent, reproducible, and sustainability-oriented forecasting workflow rather than a final benchmarking result. Future research should extend the dataset, strengthen statistical evaluation, and compare the framework against broader baseline and hybrid models.

ACKNOWLEDGMENTS

The authors gratefully acknowledge the Ministry of Education, Culture, Research, and Technology of Indonesia for supporting this study.

FUNDING INFORMATION

This research was funded by the Ministry of Education, Culture, Research, and Technology of Indonesia through the 2024 Fundamental-Regular Research Scheme under grant numbers 108/E5/PG.02.00.PL/2024, 082/LL6/PB/AL.04/2024, and 002/K-PL/LPPM/STMIK-SN/2024.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Iwan Ady Prabowo	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	✓
Hendro Wijayanto	✓	✓				✓		✓	✓	✓	✓	✓	✓	
Teguh Susyanto			✓	✓		✓	✓			✓	✓			✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that there is no conflict of interest regarding the publication of this article.

DATA AVAILABILITY

The data supporting this study, including monthly visitation counts, preprocessed series, and decomposition results for the three tourism sites in Sidowayah Village, are available from the corresponding author, [IAP], upon reasonable request. Public release is currently restricted because the data are managed jointly with local tourism stakeholders. Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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